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Color Vision System for Estimating Citrus Yield in Real-time

Palaniappan Annamalai, Graduate Research Assistant (E-mail: palani@ufl.edu)

Won Suk Lee, Assistant Professor (E-mail: wslee@ufl.edu)

Thomas F. Burks, Assistant Professor (E-mail: tfburks@mail.ifas.ufl.edu)

Agricultural and Biological Engineering, University of Florida, Gainesville, FL 32611.

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Abstract. *A machine vision system utilizing color vision was investigated as a means to identify citrus fruits and to estimate yield information of the citrus grove in real-time. Images were acquired for 98 citrus trees in a commercial grove located near Orlando, Florida. The trees were distributed over 48 plots evenly. Images were taken in stationary mode using a machine vision system consisting of a color analog camera, a DGPS receiver, and an encoder. Non-overlapping images of the citrus trees were taken by determining the field of view of the camera and using an encoder to measure the traveled distance to locate the next position for acquiring an image. The threshold of segmentation of the images to recognize citrus fruits was estimated from the pixel distribution in the HSI color plane. A computer vision algorithm to enhance and extract information from the images was developed. The total time for processing an image was 119.5 ms, excluding image acquisition time. The image processing algorithm was tested on 329 validation images and the* R^2 *value between the number of fruits counted by the fruit counting algorithm and the average number of fruits counted manually was 0.79. Images belonging to a same plot were grouped together and the number of fruits estimated by the fruit counting algorithm was summed up to give the number of fruits/plot estimates. Leaving out outliers and incomplete data, the remaining 44 plots were divided into calibration and validation data sets and a model was developed for citrus yield using the calibration data set. The* R^2 *value between the number of fruits/plot counted by the yield prediction model and the number of fruits/plot counted by hand harvesting for the validation data set was 0.53.*

Keywords. Citrus, Color Vision, Yield mapping, Precision agriculture, Image processing

Introduction

Competitive farmers strive to increase crop yields while minimizing costs. With the advent of mechanization of agriculture and a trend towards larger equipment, farmers were able to cultivate very large areas but many continued to treat their larger fields as a single management unit, thus ignoring variability found within a specific field. Precision farming, sometimes called site-specific farming, is an emerging technology that allows farmers to reduce costs through efficient and effective application of crop inputs for within-field variability in characteristics like soil fertility and weed populations.

One of the major agricultural products in Florida is citrus. Florida's citrus industry produced about 12.4 million metric tons of citrus in the 2000-2001 season accounting for 76 percent of all citrus produced in the U. S. (Florida Agricultural Statistics Service, 2001). Currently citrus groves are managed as blocks and the variability found within this unit is not generally considered for grove management. Citrus trees with sufficient water and nutrients grow stronger, better tolerate pests and stresses, yield more consistently, and produce good quality fruit than trees that are treated to excessive/deficient irrigation or fertilization. To a citrus grower who deals with thousands of trees in many blocks, site-specific management or precision agriculture provides the ability to apply technology and to manage inputs as closely as required within a given area. This management of field variability could improve fruit yield, quality, and income and limit negative impacts on sensitive environments. Among precision technologies, yield mapping is the first step to develop a site-specific crop management.

Currently, a commercial citrus yield mapping system, named as Goat, (GeoFocus, LLC, Gainesville, FL) is the only available citrus yield mapping system. This system is attached to a "goat" truck used primarily in citrus harvesting operations. In this system, the goat truck operator is required to push a button to record the location of every tub, which may be forgotten and often becomes a major source of error. Yield information is available only after the fruits are harvested and this system gathers yield data from multiple trees rather than from each individual tree.

The overall goal of this research is to develop a real-time yield mapping system using machine vision and to provide yield of a grove on-the-go when mounted on a truck and driven in-between the rows. The system will identify citrus fruits from images using color information in real-time. The system will estimate citrus yield for a single tree while citrus yields are currently determined based on whole block or grove. More specifically, the objectives in this research are to:
1) Develop a hardware system consisting of a color CCD camera, an imaging board, an encoder, a DGPS receiver and an algorithm to take non-overlapping images of the citrus grove, 2) Develop an image-processing algorithm to identify and count the number of citrus fruits from an image, 3) Develop a yield estimation model that will predict the number of fruits per tree based on the images of the tree.

A main advantage of the proposed system is that it would provide single-tree yield and could estimate citrus yield before the actual harvesting schedule. Yield information thus estimated could then be used for deciding various citrus management practices such as the amount of irrigation, application of herbicide to the plants and finally for scheduling grove equipment and pickers.

Background

Precision agriculture is a management philosophy that responds to spatial variability found on agricultural landscapes. Among precision agriculture technologies, yield mapping is the first step in site-specific crop management that helps to decide whether to apply precision agriculture technologies on a specific field. Numerous yield monitoring and yield mapping systems have been widely researched and commercialized for various crops over the last one and a half decades. Yield mapping during grain harvesting (Schueller and Bae, 1987; Searcy et al., 1989) has been extensively studied and adopted. Examples of yield mapping for other crops include cotton (Wilkerson et al., 1994; Roades et al., 2000), potatoes (Campbell et al., 1994), tomatoes (Pelletier and Upadhyaya, 1999), and silage (Lee et al., 2002).

The preliminary on-tree value of all citrus for the 2000-01 season in Florida was $760 million. In spite of the widespread economic importance of the citrus industry, currently the Goat system is the only commercial yield mapping system for citrus. Citrus yield monitoring systems have been under development for several years. Earliest known yield monitors for citrus were developed by Whitney et al. (1998 and 1999) and Schueller et al. (1999). In the Goat yield mapping system, yield is measured by mapping the location of a tub as it is picked by a truck. One advantage of this system is that there is no need for any change in the harvesting practice involving many field workers who are often relatively untrained in managing sophisticated equipment.It was noted that this system occasionally produced incorrect maps due to the fact that occasionally the truck driver failed to record the location of the tub because of the rush in harvest or other factors. To avoid the previously encountered problem, an automatic triggering system (Salehi et al., 2000) was developed to record the location of the tub but that system didn't record some tub locations due to problems with hardware connections.

The economic value of the citrus industry in Florida makes precision farming a viable technology for enormous development. Recognizing citrus fruits on a tree is the first major task of a yield mapping system using a machine vision system. Automatic visual identification of fruit is complicated by variation in lighting conditions from bright sunlight on the outer parts of the canopy to deep shadow within the canopy. Citrus fruits often grow in clusters and also some of the fruits are occluded by branches and foliage. Fruit distribution was studied (Juste et al., 1988) with Salustiana and W. navel using a system of cylindrical coordinates and it appeared that approximately 80% of fruits were at a distance of 1 m - 1.4 m from the outer canopy. But in the case of Mandarins most of the fruits were at a distance of 0.75 m from the outer canopy. Distribution of fruit clusters in citrus trees was studied (Schertz and Brown, 1966) for six navel orange trees in Tulane County, California.

Some of the earlier studies regarding fruit recognition were conducted for apple, citrus and tomatoes. Parrish and Goskel (1977) developed the earliest prototype for an apple harvester and studied the feasibility of harvesting methods based on pictorial pattern recognition and other artificial intelligence techniques. Whittaker et al. (1987) used fruit shape rather than the color information to detect tomatoes. This method could be used even in the presence of interferences caused by bright reflection and when fruits were shaded. Before applying circular Hough transform, the image was passed through a sobel gradient operator, which calculated the gradient magnitude and direction at each pixel point. Using this method, partially occluded fruits could also be detected.

Slaughter and Harrell (1987 and 1989) were involved in the development of a robotic fruit harvesting system and presented two approaches for detecting the fruit in an image based on color information. In the first approach (Slaughter and Harrell, 1987), the hue and saturation components of each pixel were used as features to segment an image by applying a traditional classification in a bi-dimensional feature space. The segmentation was carried out using a maximum and minimum threshold for each feature. Since color segmentation required some form of illumination control, they used an artificial lighting system. In the second approach (Slaughter and Harrell, 1989), a classification model was developed for discriminating oranges from the natural background of an orange grove using only color information. A Bayesian classifier was used in the RGB color space and fruits were segmented out from the background by checking whether they belonged to the fruit class or not. A reference table was created for various classes with the Bayesian classification technique.

Methods and Materials

The yield mapping system was tested in a commercial grove (Conserve II), which was located near Winter Garden, Florida. The grove consisted of 48 plots and there were 24 trees in each plot, with Hamlin oranges on three rootstocks: Cleopatra mandarin (C.Reticulata), Swingle citrumelo (Citrus paradisi Macf. x Poncirus trifoliata [L] Raf.) and Carrizo citrange (Citrus sinensis x Poncirus trifoliate). Each variety of rootstock was planted in 16 plots. Out of every plot, two trees were selected for the study. These two trees were always side by side and planted in a single row. A 4x4 truck was used for driving inside the grove. The complete setup, consisting of a desktop computer, a control box for an encoder (Model: CI20, Stegmann, Dayton, OH) and a camera (Model FCB-EX780S, Sony, New York, NY), and a DGPS receiver (model: AgGPS 132, Trimble,Inc., Sunnyvale, CA), was kept on the rear of the truck, Figure 1. A metal frame attached to the rear of the truck was used to carry a generator, the source of power supply for the entire setup and this metal frame moved in tandem with the truck. The camera and the DGPS receiver were attached to a metal pole that was supported to the tailgate of the truck. The metal pole was 4.9 m high and the camera was 5.2 m above the ground. The camera was placed at 45-degree angle relative to the ground with the intention to cover a maximum section of the tree canopy.

Figure 1. Experimental setup.

Image Acquisition

For developing a citrus fruit recognition algorithm, images were taken in stationary mode using an analog camera with 640 x 480 pixels. A total of 354 images were taken during the end of the citrus harvesting season over two days during the last week of December, 2003 and the first week of January, 2004. The images were taken in natural day light condition. Brightness and shutter speed were adjusted for each plot before acquiring images. During the experiment, shutter speed was varied between 1/1000 to 1/15 sec. Higher shutter speeds were required during bright day light condition and lower shutter speeds were useful during late afternoon to obtain good images with approximately unvarying brightness.

Development of the Fruit Counting Algorithm

The current implemented system is using HSI (hue, saturation, and intensity) as the color space. The steps in the fruit recognition algorithm are to identify fruits from an image and process the results to remove noise and to improve precision in counting the number of fruit. In this research, the object of interest was a citrus fruit and the background included citrus leaves and branches. The simplest way to segment an image is by a gray level threshold or global threshold. Unfortunately, the fruit portion, the leaf portion, and the background are not easily differentiated using this method because the gray level histogram or color histograms of these features are not unimodal. To develop a system to identify and count citrus fruit in an image, various objects in typical citrus grove scene should be collected and analyzed. In the later stage when the system was developed, it should be tested on similar images to verify and compare the performance of the proposed system. For these reasons, the images were divided into calibration and validation data set. The pixels were classified into three classes: C (citrus fruits), L (leaf), and K (background). The RGB and HSI values of each pixel were obtained using a program written in VC++ (Microsoft Corporation, Redmond) with the Matrox Imaging Library (Matrox Imaging, Quebec, Canada) for three different classes. The pixel values were stored in separate text files for different classes and processed using Microsoft EXCEL (Microsoft Corporation, Redmond).

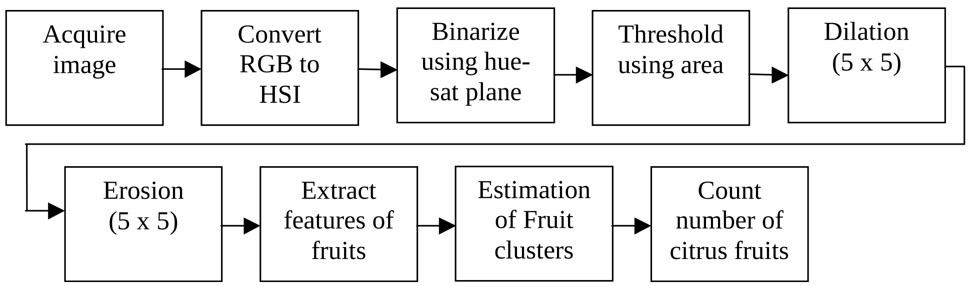


Figure 2. Image processing steps of the fruit counting algorithm.

Pixels in the three classes C, L and K were chosen manually by inspecting from the images in the calibration image set. Pixels were plotted for various combinations of color components in the RGB and HSI color space. Binarization was carried out in the color plane containing a clear distinction between the fruit and background, resulting in white pixels representing the fruit and black pixels for all other classes. Due to the dissimilarity in illumination between the images and the presence of some dead leaves, certain pixels were falsely classified as fruits. Using the set of calibration images, immediately after binarization, a threshold was applied based on area of the selected features to remove false detections. In order to process binary images, the following operations were performed: erosion, dilation and closing. The kernel sizes for filling the gaps were determined by applying kernels of various sizes and of various orders over the calibration images. These image processing steps are shown in Figure 2. Citrus fruits were identified using blob analysis and in this method, connected fruit pixels were treated as a single fruit. Fruit features such as area was extracted for all fruits and stored in a text file for post processing. Fruit area is defined as the number of pixels in a connected region.

Image Processing Time

Processing time is a major concern in a real-time machine vision application. A 750 MHz Pentium processor was used to process an image and the processing time of each image-processing step was measured using the computer clock. Each step was measured 10 times and was averaged from 10 executions. Each image had 640 x 480 pixels and every pixel has to undergo many comparisons based on its relative position in the hue-sat color plane to be classified to one of the three classes. To reduce the processing time, every pixel was compared with background category initially since the percentage of background pixels was high in an image. This optimization considerably reduced the time for processing an image.

Experimental Procedure

The encoder was calibrated before the actual experiment in the citrus grove. Pulses from the encoder were read for known distance three times and the average of those values were taken to be the encoder output for that particular distance. Two channels were read from the encoder and the phase between the channels helps to identify whether the wheel was moving in the forward direction or in reverse direction. Once the camera was mounted on the top of the pole, the camera field of view was measured and the width and height of the imaging scene were calculated. Based on the width of the image scene, the encoder was programmed to prompt the user when the required distance has been traveled from the current imaging location to take subsequent non-overlapping image. After aligning the first image with the tree, the truck was driven very slowly (2.2 m/s) and the pulses from the encoder were read continuously with a 20 ms time interval to measure the distance traveled from the previous imaging location. After the required distance had been traveled, subsequent non-overlapping images were grabbed along with position information from the DGPS receiver. Immediately the encoder counter value was reset to zero so that the relative distance from the new imaging position could be used as reference for the next image. The algorithm continued until the user terminated it. The height of the camera was adjusted only once at the beginning of the day and remained at the same position throughout the day.

Performance of the Fruit Counting Algorithm and Yield Prediction Model

In order to evaluate the performance of the algorithm, fruits counted by the fruit counting algorithm should have been compared with the actual number of fruits in the region covered in the image. Since it was very difficult to define the boundary of each image and count the number of fruits in the grove, the images were shown to three observers and the average of these three reading were taken as reference for the fruit counting algorithm. This arrangement was made for manual counting because there were variations in the total number of fruit perceived by human beings.Images from each plot were grouped together and the number of fruits from each plot is compared with the actual number of fruits harvested from the respective plots. Half of the total plots were used as calibration data to develop a prediction model to estimate citrus yield. The model was tested on validation data set consisting of remaining plots.

$$Error_{\mathrm{Image}}(\%) = \frac{MV - MC}{MC} \times 100 \qquad Error_{\mathrm{Plot}}(\%) = \frac{Y_E - Y_A}{Y_A} \times 100$$

where MV = number of fruits counted by the machine vision algorithm, MC = average number of fruits counted manually, Y_E = Estimated yield by the machine vision system, Y_A = Actual yield by hand harvesting.

Results and Discussions

Binarization

Using a program written with Matrox library in Visual C++, RGB & HSI components were collected for features by drawing a rectangle using a mouse. There was no distinct separation between citrus class and other classes in any of the individual color component. As a next step, gray level histograms were plotted in pairs of two color components and it was found that there existed a clear line of separation between the fruits and the background in HSI color space, Figure 3(a) and 3(b).

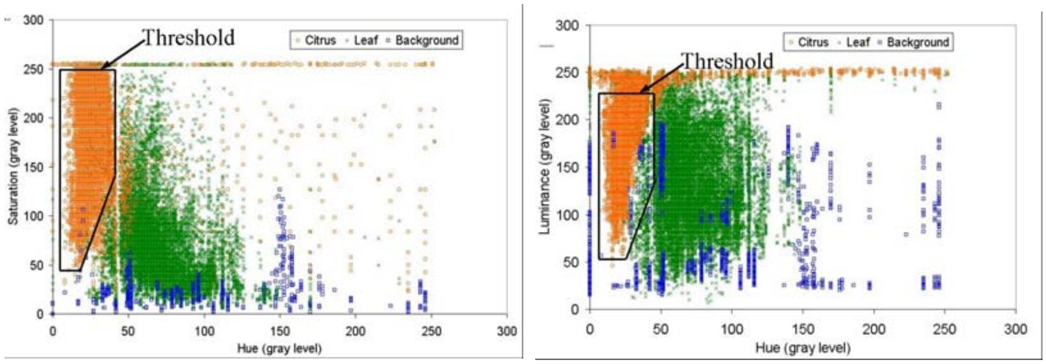
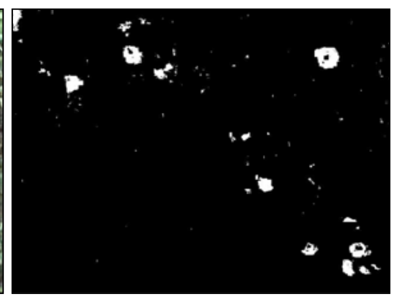


Figure 3. (a) Hue-Saturation color plane (b) Hue-Luminance color plane.

The threshold in hue-saturation color plane was carefully chosen in a conservative approach after many trials have been conducted over the calibration images. The luminance component was added to the threshold to make it less dependent on the brightness level of the image during binarization. The pixel distribution for various classes in the calibration images is shown in Table 1. Although only 58% of citrus class was captured inside the threshold, the binarization scheme was found to work very well with the validation images. The main reason behind this threshold was that the threshold contained 0% of background and 0.03% of leaves. An example of image processing steps for a typical citrus grove image is shown in Figure 4. Figure 4(a) and 4(b) shows a sample color image and its binarized image.

(a) Color image (b) Binarized image


(c) After removing noise (d) After filling gaps

Figure 4. Image processing steps of a typical citrus grove scene.

Table 1. Pixel distribution for C, L and K classes for 25 images in HSI color plane.

Pixel Category	Citrus class		Leaf class		Background class	
	Number of pixels	Percentage	Number of pixels	Percentage	Number of pixels	Percentage
Inside threshold	15875	58.1%	68	0.03%	0	0%
Outside threshold	11438	41.9%	23347	99.7%	8165	100%

Preprocessing

The binarized images contained noise mainly due to the little overlap of the leaf class with the citrus class in the hue-saturation color plane. By applying a threshold of 100 pixels based on area of the extracted features, these noises were removed from the images. The resulting image after removing noise is shown in Figure 4(c). In the above processed image, there were cases in which a single fruit occluded by small leaves were counted as more than one fruit. To overcome this problem, a set of dilation and erosion with a kernel size of 5x5 pixels was applied to the images, resulting in the final processed image as shown in Figure 4(d). These images could then be used to count the number of citrus fruits by the algorithm.

Recognition and performance of the fruit counting algorithm

Citrus fruits were identified using blob analysis and in this method, connected fruit pixels were treated as a single blob and the total number of blobs gave the number of fruits in the image. It should be noted that there was very few over estimation and many under estimation by the algorithm. The main reasons for overestimation were: 1) When a single fruit was hidden by many leaves and the separation between the small blobs was more than 25 (5x5) pixels, they were counted as different fruits, 2) Small fruits were not clearly visible in manual counting however they were counted as fruits by the machine vision algorithm, 3) In some images, there were many fruits hidden in dark background. Reasons for underestimation were: 1) Some fruit clusters were counted as single fruit by the machine vision algorithm due to connectivity 2) When the visible portion of a fruit was very small, it would have been removed since a threshold in area was carried out to remove noise. Since the area of the fruit clusters were relatively large in size compared to other single fruits, modifications were made in the fruit counting algorithm to rectify for the underestimation problem. As it was found from the calibration images that there were a few fruits completely visible and all the remaining fruits were mostly hidden by leaves, average size of a fruit in an image was calculated based on the five largest fruits in an image. If the average area was less than 200 pixels or if the total number of fruits in an image was less than 10, then it was decided to end the fruit counting procedure. This was because it would be difficult to identify fruit clusters when the leaves might have hidden all the fruits or the imaging scene would have been at a large distance from the camera. Otherwise the following fruit cluster estimation module was conducted.

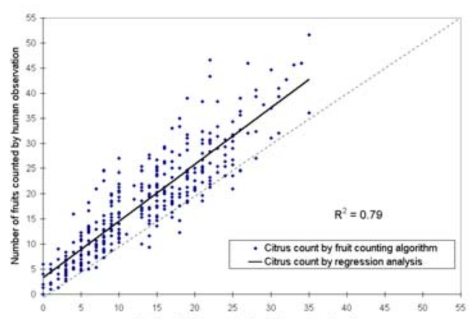


Figure 5. Regression analysis between the number of fruits counted by human observation and the number of fruits counted by the fruit counting algorithm.

A threshold was calculated based on the average area of fruit and if the fruit area was more than the threshold, it was identified as a fruit cluster and counted as two fruit instead of one. Fruit clusters were counted only as two instead of many fruits because of the difficulty in defining a threshold in area for multiple fruits. The threshold was selected with trial and error using the calibration images. The percentage error was as low as 0% and as high as 100% in cases where there were 1 or 2 fruits and the algorithm identified none. A regression analysis was conducted between the number of fruits by manual counting and the number of fruits counted by the fruit counting algorithm for 329 validation images, Figure 5. The R^2 value for the regression analysis was 0.79.

Execution time for the algorithm

Table 2 shows the average execution time for each image-processing step. Conversion from RGB to HSI color space took a major segment of the execution time since the algorithm needed to compute 640 x 480 pixels for an image. Binarization was carried out using software that consisted of checking hue, saturation, and luminance gray levels of each pixel value with the threshold and classifying accordingly. The time for initialization was also measured and it was 80 ms. Average execution time including all steps was 119.5 ms. During real time field-testing, image acquisition time needs to be added

Table 2. Execution time for each image processing step.

Image processing step	Avg. Execution time (ms)	Percent of total time (%)
Conversion from RGB to HSI	78.8	65.9
Binarization	28.4	23.8
Remove noise	6.3	5.3
Fill gaps	3.8	3.2
Extract features and count fruits	2.1	1.8
Total time	119.5	100.0

Encoder Calibration

The encoder was calibrated in the grove before the field-testing of the algorithm. The truck was driven for predefined distances three times and the average of the number of pulses generated by the encoder was used as the reference number of pulses for each distance. The R^2 value for the regression analysis was 0.99.

D = 0.00804Np - 0.02 where D = Distance, Np = Number of pulses

Prediction of number of fruits/plot

In the grove where the citrus yield mapping system was tested, two trees in each plot were designated for hand harvesting. Those trees were hand-harvested on Feb. 6, 2004 and number of fruits per plot (*NA)*, average weight of fruit in a plot, minimum diameter of fruit in a plot, maximum diameter of fruit in a plot, average diameter of fruit in a plot, average boxes per tree per plot and number of boxes per plot were recorded. This information was used as a reference for the yield prediction model. There were cases in which images of entire plot was not taken. For example, images were taken only on west side of plots 82, 43 and 83 since there were moisture sensors (tensiometers) on the other side of the plot. Hence these three plots 82, 83, and 43 were removed from the data analysis. Regression analysis was carried out between *NA* and the number of fruits/plot predicted by the fruit counting algorithm. It was found out that there were an outlier for plot 7 and subsequently it was removed from further data analysis. Fruit/plot were predicted based on three variables: 1) Number of fruit estimated using fruit counting algorithm (NP_{fruits}) 2) Number of citrus pixels/plot estimated using fruit counting algorithm (NP_{pixels}) 3) Number of fruits/plot estimated using citrus pixels/plot data ($NP_{fruits\text{-}pixels}$).

Fruits/plot data for the remaining 44 plots were divided randomly into two groups, and one was used as calibration data set and the other was used as validation data set. Images belonging to a same plot were grouped together and the number of fruits estimated by the fruit counting algorithm was summed up to give the number of fruit/plot estimates, using the following variables: NP_{fruits}, NP_{pixels}, and $NP_{fruits\text{-}pixels}$. Regression analysis was conducted between *NA* and the variables: NP_{fruits}, NP_{pixels}, and $NP_{fruits\text{-}pixels}$ for the calibration data set, Figure 6(a), 6(b) and 7(a). The R^2 value for the regression analysis between actual harvested fruit/plot and NP_{fruits} was 0.46. The R^2 value for the regression analysis between actual harvested fruit/plot and NP_{pixels} was 0.28.

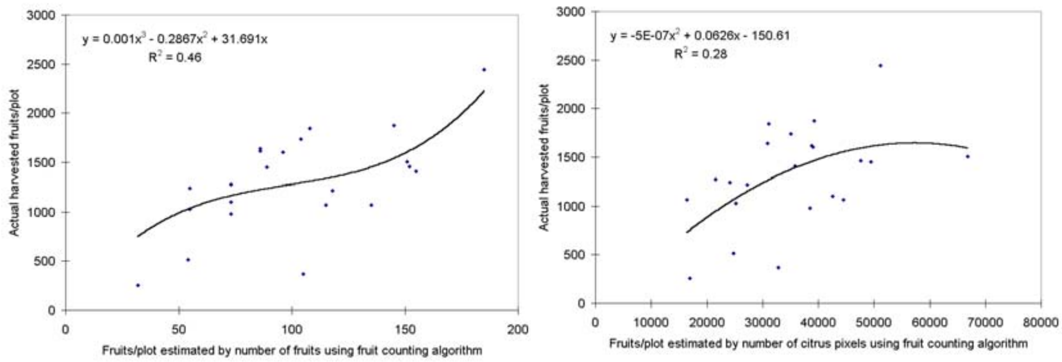


Figure 6.(a) Regression analysis between *NA* and NP_{fruits} *(b)* Regression analysis between *NA* and NP_{pixels}

Relation between a pixel size and its corresponding size in the imaging scene was calculated. Actual size of an image with 640 x 480 pixels corresponded to an imaging scene of 1.7 m long and 1.25 m high. As the average size of a fruit from each plot was known, area of a fruit in a plot was calculated in terms of pixels. Then the number of fruits in a plot was determined from the total number of citrus pixels/plot, and was used to estimate the number of fruits in a plot. The yield prediction model was developed using NP_{fruits} model since the R^2 value was the highest among the three approaches. Citrus yield is calculated as number of citrus fruits per unit area. The distances between citrus trees in the grove were 3.05 m in-row and 6.1 m between-rows. The number of fruits/plot estimated using fruits based on pixels/plot from the machine vision algorithm was used in the yield prediction model. For this particular experimental setup, yield was calculated as

$$Y_E = \frac{NP_{fruits-pixels}}{3.05 \text{ x } 6.1\,(m^2) \text{ x } 2\,(trees)}, \qquad Y_A = \frac{NA}{3.05 \text{ x } 6.1\,(m^2) \text{ x } 2\,(trees)}$$

The percentage error was as low as 1.6% for plot 35 and as high as 451.2% for plot 33. The main cause for the high error rate was due to the fact that using a single camera, it was not possible to cover the entire citrus tree. Fruits that were inside the canopy would have been completely occluded by leaves in the images. Hence the fruit counting algorithm was not able to identify these occluded fruits.

Yield estimation model depends on the imaging scene of a particular tree. If large distribution of fruits on a particular tree were not captured on the image, the model would have predicted very less yield than the actual harvested yield. Since fruits were stretched throughout the tree canopy in irregular patterns, yield estimation based on portion of a tree was not very successful. Before the experiment, it was considered that keeping the camera 5.2 m high and focusing at 45 degree with respect to ground would cover majority of the tree canopy. But during the field-testing, it was found that the resolution of the image was not good with this setup. Hence to take clear images, the camera lens was zoomed in by a factor of two thus covering small percentage of the tree canopy. A regression analysis was conducted between the yield estimated by the

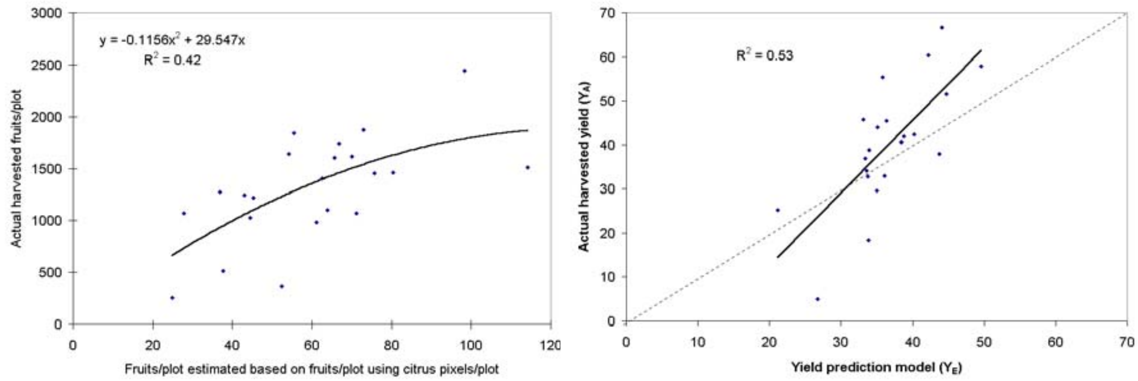


Figure 7. (a) Regression analysis between *NA* and $NP_{fruits\text{-}pixels}$ *(b)* Regression analysis between yield prediction model and the actual harvested yield.

yield prediction model and the actual yield for 22 plots, Figure 7(b). The R^2 value for the regression analysis was 0.53, RMSE was 50.3 fruits/meter^2 and CV was 84.6%. If multiple cameras were used to cover the majority of the tree canopy, then the model could be used to predict yield with improved accuracy.

Summary and Conclusion

The fruit counting algorithm developed in this research verified the feasibility of developing a real-time machine vision system to estimate citrus yield on-the-go. The algorithm consisted of image acquisition, binarization of color image in hue-saturation color plane, preprocessing to remove noise and to fill gaps, and, finally, counting the number of fruits. Blob analysis was used to count the citrus fruits and the total number of blobs gave the number of citrus fruits in an image. A cluster of fruits was identified partially using the average area of a fruit and counted as two fruits instead of one in the algorithm. The total time for processing an image was 119.5 ms. The algorithm was tested on 329 validation images and the R^2 value between the number of fruits counted by the machine vision algorithm and the average number of fruits counted by human observers was 0.79. The variation in the number of fruits correctly classified was partially due to clusters of citrus fruits, uneven lightning and fruit occlusion. Images belonging to a same plot were grouped together and the data from 22 plots were used to predict fruit/plot using three variables: 1) NP_{fruits} 2) NP_{pixels} 3) $NP_{fruits\text{-}pixels}$.

Yield prediction model was developed using $NP_{fruits\text{-}pixels}$ variable. The model was applied over 22 validation plots and the R^2 value between the yield predicted by the model and the actual harvested yield was 0.53. The results indicate that the yield prediction model could be enhanced by using multiple cameras for covering the majority of tree canopy. Highly non-uniform illumination in an image presented a problem for color vision based segmentation approach. One improvement to the present system would be to improve the imaging of natural outdoor scenes with wide variation in illumination. Automatic brightness control before imaging could be implemented by using a phototransistor to measure the intensity of the imaging scene and sending control to the camera to change its shutter speed/brightness level.

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