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Machine vision system for early yield estimation of citrus in a site-specific manner

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Abstract. *Detecting immature green citrus at an early stage for yield forecasting can help growers expect how many fruit they can harvest at the end of the year. Also, it can provide an in-field spatial variability of fruit that can be used for providing site-specific management of citrus trees to increase yield and profit. Yield forecasting using the machine vision technology has been a promising but challenging research area. In this research, an algorithm using 3D geometric features was developed to identify immature green citrus far in advance of harvesting. The specific objectives were to develop a robust machine vision algorithm for images that had more complicated backgrounds than previous studies and to build an algorithm to have stable performances in varying illumination conditions. The machine vision algorithm was fully automatic and consisted of three steps, 1) illumination enhancement of the RGB image, 2) potential area finding using depth information and 3) classification of fruit and background. A total of 93 images were acquired and used to develop and validate the algorithm. The final result was analyzed using the correctly identified fruit and false positives. Average correct identification rate and false positive rate were 72.1% and 23.2%, respectively.*

Keywords. *Green citrus detection, Image processing, Kinect sensor, Machine learning, Precision agriculture, RGBD image, Yield forecasting.*

Introduction

Estimation of yield is always top priority for crop growers. Especially, accurate estimation of crop yield in smaller areas has been demanded from crop growers and packers (Bellow, 2007). In recent years, new methods for yield monitoring or prediction of potential yield prior to harvesting is getting more attention because current estimation methods are based on historical yield data collected manually by sampling and several assumptions that may mislead users (Lee and Herbek, 2005). Like other agricultural industries, the citrus industry in the United State is asking for tools for forecasting potential yield because prompt and accurate estimation of potential yield can help citrus growers to manage their groves, such as preparing tree inventory, fertilizing and treating diseases. Also, the immature citrus detection algorithm can be used as a prescription map which is one of key concepts in precision agriculture. The precision agriculture practice enables not only reducing production cost but also producing better quality of crops and maintaining the quality of the environment by modifying application rate based on the amount of expected crops in their groves (Stafford, 2000). However, manual examination of the amount of citrus is a time-consuming and labor-intensive task. Also, the manual inspection may include inspector bias and increase the production cost due to labor costs. Using machine vision technology, the manual inspection of estimating the amount of future yield can be replaced with an automated method. The automated system can be used in commercial citrus groves and reduce the costs by reducing the needed human workforce and performing intensively repetitive and complicated tasks in an inexpensive, faster and more accurate way.

Yield forecasting using a machine vision technology has been a promising but challenging research area. Previously, Kurtulmus et al. (2011), Bansal et al. (2013) and Sengupta and Lee (2014) studied immature citrus detection in regular RGB images. In those studies, color with shape or texture features were used to characterize the immature citrus fruit from the background. Kurtulmus et al. (2011) utilized color and texture to detect immature citrus in their images. They developed an algorithm using ‘eigenfruit’ approach inspired by the ‘eigenface’ face recognition method. Shifting a sub-window in intensity and saturation components was used for the detection and majority voting was conducted to determine final results. A total of 64 images were used and they reported 75.3% of the actual fruits were successfully detected. In a study by Bansal et al. (2014), a more efficient and simple algorithm to detect green citrus was developed. The machine vision algorithm consisted of calculating fast Fourier transform leakage for fruit and leaves and thresholding obtained from comparing the percent leakage of fruit and background. In their algorithm, 11 images were used for training the algorithm and a set of 60 images were used for validation. The correct identification rate for a validation set was 82.2%. Sengupta and Lee (2014) proposed an algorithm using shape and texture information. The circular Hough transform was used to find potential areas of fruit and texture and scale invariant keypoints classification were used to reduce false positives. Majority voting was then adopted to make final decision. The rate of correctly identified fruit was 81% among 62 images.

However, these techniques using regular RGB images required complicated processing steps due to the lack of distinct features of the citrus in RGB images. In some of the above studies, this problem caused a tendency that the objective of the algorithms was to detect the citrus that were not fully ripen so the colors of the citrus were partially yellowish. The overall goal of this project was similar to the previous studies, to develop a system that can identify immature green citrus on trees. However, in this research, an algorithm using 3D geometric features was developed to identify immature green citrus far in advance of harvesting which was significantly smaller and greener compared to the above studies. The specific objectives were to develop a robust machine vision algorithm for images that had more complicated backgrounds and to build an algorithm to have stable performances in varying illumination conditions.

Materials and Methods

Hardware and image acquisition

A prototype hardware system (figure 1) was developed with an electric cart (4x4 Judge, Kings of cart, Columbia, SC), a mounting frame, a laptop (Intel(R), Core i5 processor with a 6 GB RAM and a 64-bit Windows 8.1 operating system) and a camera (Kinect for windows v2, Microsoft, Redmond, WA, figure 1a). The camera had functions of acquiring RGB, infrared and depth images. Images were acquired while it was installed on the vehicle (figure 1b) and also while it was held by hand using a monopod for fruit located too far to be reached by mounting frame on the cart (figure 1c). The camera was located at 50-60 cm distance from the canopy. Image acquisition software was developed in C++ using SDK provided by Microsoft. A field experiment was conducted during daytime on May 7, 2015 at an experimental citrus grove in Plant Science Research & Education Unit (PSREU, Citra, FL). A variety of the citrus in the acquired images was Navel and a typical length of the citrus diameter was about two to three cm. A total of 93 images containing a scene of canopy with leaves and green citrus fruits was acquired and each image had a GPS coordinate recorded separately to store location where images were taken.

Figure 1. Prototype system for estimating number of small green citrus fruit in the canopy: (a) a camera used to capture images of canopy (Microsoft image) (b) side view of electric cart with a camera and (c) illustration of manual image acquisition.

Machine vision algorithm to detect immature green citrus on trees

A machine vision algorithm was developed and tested using Matlab R2014b on a desktop computer (Intel(R), Core i7 (3.6 GHz) processor with an 8 GB RAM and a 64-bit Windows 7 operating system). The machine vision algorithm consisted of 1) illumination enhancement of the RGB image, 2) potential area finding using depth information and 3) classification of fruit and background. The RGB images were taken without an external light source causing varying illumination conditions among regions of the images (figure 2a). An image enhancement algorithm was applied using contrast limited adaptive histogram equalization mainly for brightening dark areas in images (figure 2b). The RGB image had a resolution of 1920 by 1080 pixels and each pixel in a RGB image was mapped to a depth value from different sensor in the same camera with a resolution of 512 by 424 pixels (figure 3a). The mapped depth value can be used to calculate 3D geometric feature of objects. In figure 3b, citrus fruit had different iso-level contour pattern, stacked circles with decreasing diameters in direction from perimeter towards the center of the fruit (red arrow). On the other hand, background and leaves had iso-level contours that were more random shapes.

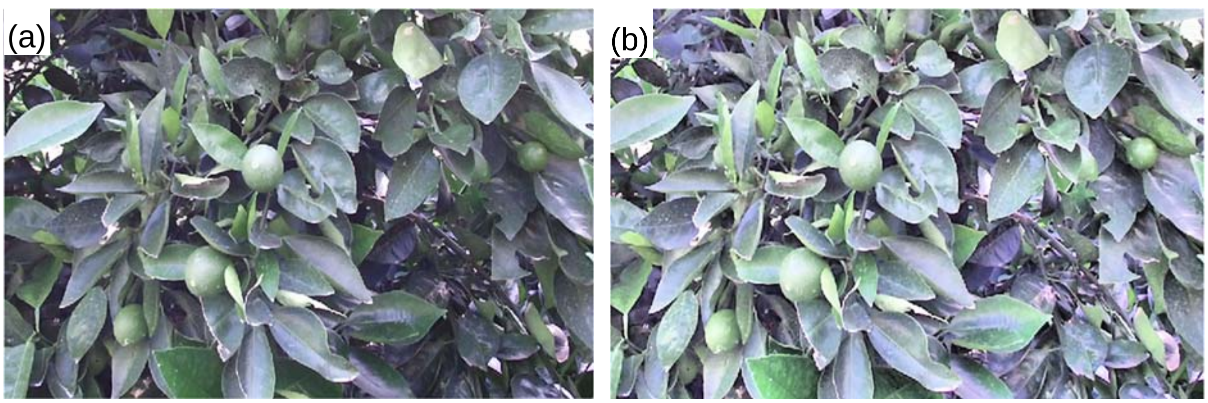

Figure 2. A part of example RGB and enhanced images

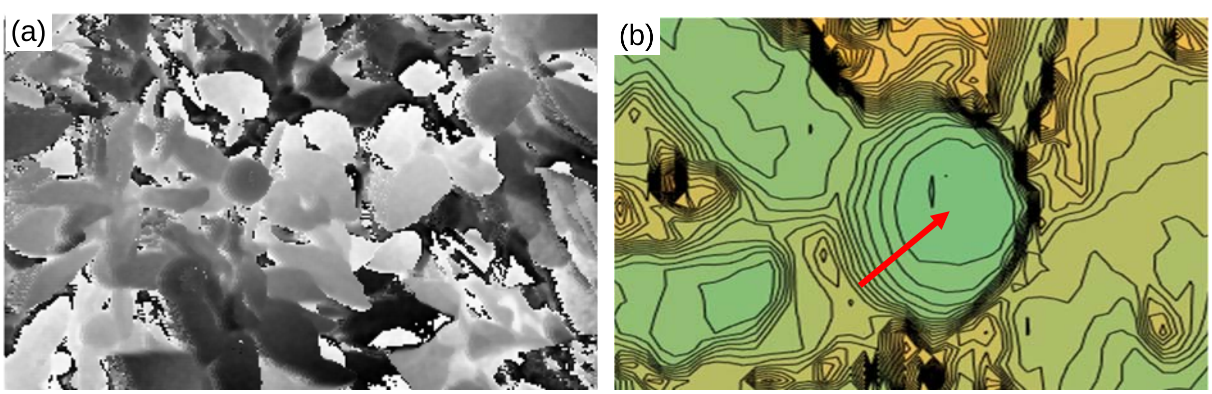

Figure 3. (a) A part of depth image and (b) iso-level contour map of citrus fruit using mapped depth values

In the developed machine vision algorithm, the 3D geometry of an image scene was quantified by calculating the gradient vector field of the depth image (equation 1). In the equation 1, $\vec{V}$ represents a pair of gradient vector components (u, v) where u and v are partial derivatives of depth D in the x and y directions, respectively.

Gradient: $$\vec{V} = \nabla D = \left(\frac{\partial D}{\partial x}, \frac{\partial D}{\partial y}\right) = (u, v) \quad (1)$$

Due to the structure of the depth sensor, closer objects had a smaller distance value and consequently the citrus had a convex parabolic shape in the 3D depth map. This geometric characteristic caused the gradient vector field plot of citrus in 2D appeared to stretch out from the center of the citrus to the direction of its closest perimeter pixel (figure 4a). Then, all vectors were rotated in clockwise direction with fixed origin. This step led the gradient vector field of convex paraboloid surface to show a pattern of clockwise rotation (figure 4b). On the other hand, a concave paraboloid surface had a pattern of counter-clockwise rotation. This features can be compared with each other by vorticity formula in equation 2, which represents angular velocity (magnitude and direction) of a pixel caused from neighboring vectors. Using the patterns, convex paraboloid surfaces in the image were found and considered as potential areas of citrus. The centers of potential areas were found using highest entropy pixel in the region since the increasing rate of vorticity magnitude tends to get larger along with the direction from the perimeter to the center causing higher entropy values. After identifying the centers, a small mask was created and applied in the RGB image to find the circular shape using the circular Hough transform (CHT). The detected region using the CHT were considered as final candidates for classification process.

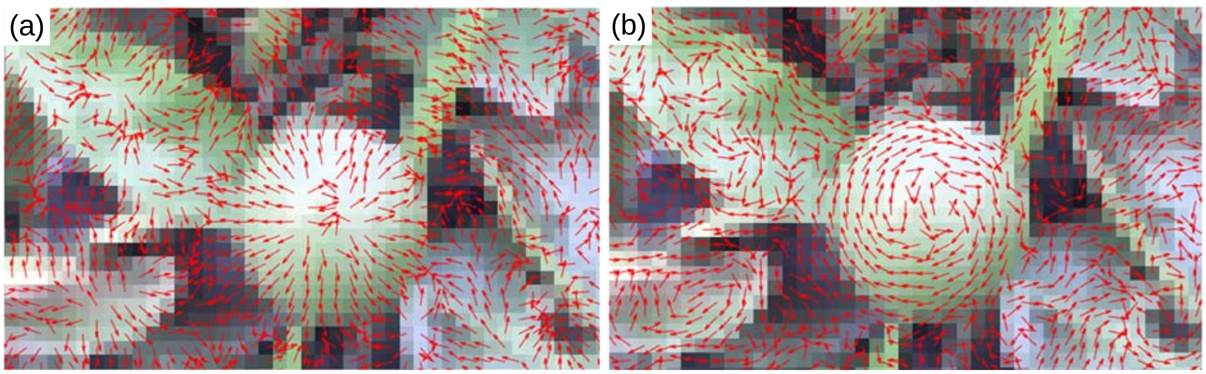

Figure 4. Example gradient vector plot of the citrus overlaid on RGB images. (a) gradient vector plot of depth without rotating and (b) gradient vectors after rotation.

Vorticity: $$\omega = \nabla \times \vec{V} = \left(\frac{\partial}{\partial x}, \frac{\partial}{\partial y}, \frac{\partial}{\partial z}\right) \times (u, v, 0) = \left(\frac{\partial v}{\partial x} - \frac{\partial u}{\partial y}\right)\vec{z} \quad (2)$$

where ∇ represents a partial derivatives operator in the x, y *and* z directions, $\times$ represents a cross product operator and $\vec{z}$ represents a unit vector in z axis.

Then, classification using a random forest classifier to detect citrus from the background with features including radius in 3D, texture information in grayscale image, depth image and gradient values in depth image. Table 1 shows a summary of features used in the classification process. A total of 13 features were used for training and validation of the classification.

Table 1. Description of features used in the Random Forest classifier.

Description of features	Number of features
Size of citrus (number of pixels in perimeter and difference in max/min depth value)	2
Mean and standard deviation in depth and grayscale	4
Mean and standard deviation in gradient magnitude	2
Mean and standard deviation in entropy of depth	2
Mean and standard deviation in entropy of grayscale	2
Number of edges inside of object	1
Total	13

Final classification results were analyzed using two criteria, 1) correctly identified fruit and 2) incorrectly identified background as citrus. A manual counting of the actual number of fruit, correctly identified citrus fruit and incorrectly detected background as citrus was conducted. Then, the correct identification rate was also computed by dividing the correctly identified citrus fruit by the actual number of fruit. Likewise, the false positive rate was calculated by dividing the incorrectly detected background by the actual number of fruit in an image.

Results and Discussion

An example image of finding potential area using the vorticity equation (equation 2) is shown in figure 6a. In the figure 6a, blue circles represent the detected potential area from the vorticity and the CHT steps. The process of finding potential area of citrus was based on 3D and 2D geometric features of citrus, convex parabolic surface and circular shape. However, some part of leaves also contained similar shape with the citrus that had convex surface in 3D and circular shape in 2D. As a consequence, not only the circles that contained citrus but also circles that included leaves and other backgrounds were detected because there was no distinction between the citrus and the leaves at this step. Therefore, detecting only citrus from the background was conducted using a Random forest classifier. Figure 6b shows an example result image after the classification. In this figure, red dotted circles indicate detected citrus and incorrectly detected potential areas in the previous steps were removed.

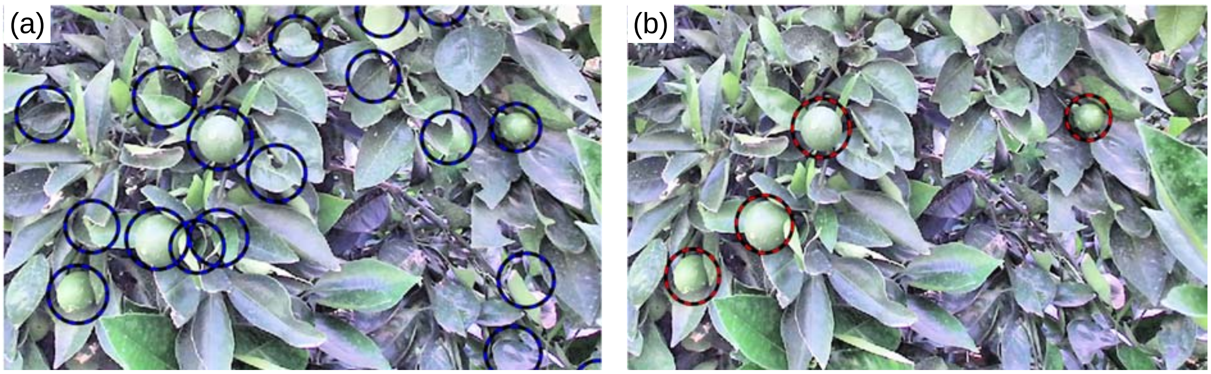

Figure 6. (a) Finding potential areas (blue circles), and (b) final result (red circle: detected fruit).

For final classification results, 93 images were divided into three folds and a 3-fold cross validation technique was applied. An analysis of the final result is shown in table 2 using the correctly identified fruit and false positives. The correct identification rate and false positive rate are also compared in parenthesis. The actual numbers of fruit were 72, 76 and 74 for each fold, respectively. For each fold, the machine vision algorithm detected 51, 53, and 56 of actual citrus fruit correctly which accounts for 70.8%, 69.7% and 75.7%, respectively. However, the detection algorithm also generated false positives, 20, 13 and 16 (29.2%, 17.1% and 21.6%) of the background objects were detected as citrus. The result shows that relatively high but acceptable rates for both correct identification and false positive rates. The main reason of higher missed fruit and false positive rates was that sizes of fruits were smaller than the leaves, so it was difficult to capture 3D geometric features of the citrus compared to the leaves. This caused confusion during classification process because some of the leaves also showed convex paraboloid shape as well and did not contain noticeable texture. However, the machine vision algorithm showed promising potential when it would be used for detecting fruit larger than the leaves.

Table 2. Image analysis results showing the number of fruit in images, correctly identified fruit, missed fruit and false positives (percentage in parenthesis).

	Fold 1	Fold 2	Fold 3	Avg.
Actual Number of Fruit	72	76	74	74
Correctly Identified Fruit (%)	51 (70.8)	53 (69.7)	56 (75.7)	53.3 (72.1)
False Positives (%)	20 (29.2)	13 (17.1)	16 (21.6)	17.2 (23.2)

Conclusion

In this study, a novel machine vision algorithm using 3D depth information was developed. Final results of the algorithm showed a capability of detecting green citrus with small size at a very immature stage. Although the machine vision algorithm used very simple but effective technique, the average rate for correctly identified fruit was 72.1%. Detecting immature green citrus at an early stage can help growers expect how many fruit they can harvest at the end of the year. Also, it can provide an in-field spatial variability of fruit that can be used for providing site-specific management of citrus trees to increase yield and profit.

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