Identification and Determination of the Number of Green Citrus Fruit under Different Ambient Light Conditions

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Abstract

Yield mapping by machine aided harvesting requires automatic detection and counting of fruit in a tree canopy. However, occlusion, varying illumination, and similarity with the background make fruit identification a very challenging task. Moreover, green citrus detection within green canopy is a very difficult problem due to the issues previously mentioned. In this study, a novel and simple technique is discussed to detect green citrus in the tree canopy under natural outdoor conditions by utilizing shape and texture information. First a shape analysis is conducted to detect as many as citrus as possible. Texture classification combined with a support vector machine, graph based connected component algorithm and Hough line detection were used to remove the false positives in the first stage. Then keypoints were detected by scale invariant feature transform algorithm and used to remove additional false positives. A majority voting scheme has been implemented to make the algorithm more robust. The algorithm was able to accurately detect and count over 81\% of citrus fruit in a validation set of images acquired from a citrus grove.

Keywords: Hough Circle, Precision Agriculture, SIFT, SVM, Tamura Texture

1. Introduction

Florida is the leading state in the United States to produce citrus, which plays a crucial part in Florida's overall economical growth. In 2009-2010, Florida accounted for 65.2\% of the total citrus production in the U. S. (USDA-NASS, 2010), while the percentage was approximately 71\% in 2008. This study was conducted to develop a yield mapping system for green immature citrus fruit so that growers can manage grove more efficiently to increase yield and profit. Due to large variability in soil type, soil fertility, tree size and other cropping conditions, citrus yield varies in the field. In order to increase yield, it would be tremendously helpful for the citrus grower if they can predict the yield before harvesting and they can use fertilizers and other resources more efficiently to increase yield at different locations.

Computer vision is commonly used for fruit identification and localization. Efficient detection of fruits and vegetables in their natural environment and calculating a reasonable estimate of the number of fruits are examples of the main applications in agriculture. Automated computer vision techniques undoubtedly offer great benefits to the farmers. Although most of the machine vision algorithms work on the images acquired by standard off-the-shelf digital cameras, there are algorithms that work on multispectral or hyperspectral images or thermal images. Combination of these types of methods is often used to achieve higher performance.

Many studies were conducted to develop citrus and other fruit detection systems using computer vision and image processing techniques. Jiménez et al. (2000) presented a review for fruit recognition systems. Schertz and Brown (1968) considered both individual-fruit harvest and mass harvest. The fruit surface was identified by photometric comparison. They reported that ten times more light reflected from a fruit than from a leaf. Parrish and Goksel
(1977) reported an experimental automated apple harvesting system in a laboratory. They used different green and red optical filters and a black-and-white TV camera to obtain images for apple orchard and developed an automated experimental system for harvesting apple. Whittaker et al. (1987) investigated an automatic system to detect tomatoes based on the shape. They implemented a modified Hough transform for circular objects to identify tomatoes even when they were occluded partially by other fruit or leaves. Pia et al. (1993) investigated the characterization of spherical objects in gray-scale images and applied their methods to detect citrus on the trees using elliptical characteristics in images. They reported a 75% success rate with an 8% false detection rate.

Annamalai and Lee (2004) developed a spectral based system to identify immature green citrus fruit in images. Using a spectrophotometer, diffuse reflectance of the green citrus fruit and leaf samples were measured and identified two significant wavelengths (815 nm and 1190 nm) to distinguish immature green citrus fruit from green leaves. Regunathan and Lee (2005) developed a citrus detection system using a color camera and ultrasonic sensors. They implemented different classification methods to differentiate fruit from the background and the segmented images were used to estimate size of the fruit. Recently Aggelopoulou et al. (2011) analyzed pictures of apple trees when they were at full bloom to find fruit density and distribution. They reported an error of 18% for the predicted yield. Kurtulmus et al. (2011) used color, circular Gabor texture and a novel algorithm named ‘eigenfruit’ to develop immature green citrus detection methods. To locate potential areas of green citrus, images were scanned with smaller sub-windows at three different scales and each sub-window was classified by the ‘eigenfruit’ approach. Majority voting was used to determine fruit object. They reported a 75.3% rate of success for fruit detection.

The objective of this study was similar to that of Kurtulmus et al. (2011), to develop a detection algorithm for immature green citrus fruit with minimum number of false positives, however with a very different approach. In this study, a novel algorithm was developed with basic shape analysis, support vector machine (SVM), Tamura texture feature, the scale invariant feature transform (SIFT), keypoints, and a majority voting. For the analysis, images taken by a typical digital camera were used, and naturally this study would be a very affordable and attractive solution for the citrus growers for estimating citrus yield well in advance before harvesting.

2. Materials and Methods

For citrus detection algorithm, images were acquired under natural daylight with a typical digital camera (PowerShot SD800IS, Canon U.S.A. Inc., USA) with a resolution of 3648 x 2736 pixels. A total of 77 images were obtained in one week period in October 2010 from an experimental citrus grove in the University of Florida, Gainesville, Florida, USA. From those 77 images, 38 images were selected randomly for training and 39 images for validation purposes. The images were resized to 800x600 pixels for computational efficiency.

For the texture training phase of the classifier, first a basic shape analysis was conducted to find tentative locations of green citrus fruit. MATLAB and Open Source Computer Vision Library (OpenCV) in C were used to develop the algorithm. Since most of the citrus had approximately circular shape, the circular Hough transform (CHT) was used to determine the parameters of a circle. Based on the approximate size of the citrus in the training images, a radius range was estimated, and a search was performed within the radius.

In the next phase of the algorithm development, supervised framework was used. First positive and negative samples were labeled to train the classifier using a small 20 x 20 pixel window from both citrus and non-citrus areas. Then a classifier was built using support vector machine (SVM) with two types of features - local texture features and Tamura texture feature. A total of 10 features for the texture elements were carefully chosen to describe local structure of the surface. They were mean of Red (R), Green (G), and Blue (B) channel,
standard deviation, entropy, threshold, contrast, homogeneity, correlation, and energy.

From the study by Tamura et al. (1978), three major texture features (coarseness, contrast, and directionality) were selected, since the other features are derivatives of these three major features.

The scale invariant feature transform (SIFT) algorithm (Lowe, 1999; Lowe, 2004) is a very useful method for detecting and extracting local feature descriptors which are invariant to changes in image translation, scaling, rotation or partial occlusion. Interest points for SIFT features are called keypoints in this framework. Keypoints were identified as the local maxima and minima of Difference-of-Gaussian (DoG) filters at variable scales. The feature descriptor of a keypoint was calculated as a collection of orientation histograms on 4x4 pixel neighborhoods each having 8 orientation bins each. All the values of these histograms were vectorized and then normalized to create a feature descriptor. This generated a SIFT feature vector with $4 \times 4 \times 8 = 128$ elements. Finally, a threshold of 0.2 was applied, and the vector was re-normalized to enhance invariance to changes due to non-linear illumination.

After the proposed algorithm was developed, the validation images were broadly classified into two categories based on a pre-determined brightness using a color histogram. Initially, CHT was run on the validation images to detect as many spherical objects as possible. Then, a maximal squared patch was taken from the inside of each circle. After dividing it into several 20x20 smaller patches, the SVM classifier was run to classify each of them, and majority of vote was taken to determine their class – fruit or leaf.

To remove false positives (objects incorrectly identified as fruit), a different approach was used for brighter and darker illuminated images. Based on the radius of detected citrus, a large patch was taken, and the false positive detection algorithm was run. Based on majority vote, false positives were removed. After this step, a SIFT keypoint detection algorithm was run on each larger patch, and the number of keypoints was counted on each larger patch. As the citrus fruit surface was relatively smooth, it would have lesser number of corners. As a result, number of detected keypoints would be lesser for the fruit surface compared to leaf surface. This was the second stage of false positive removal.

3. Results

The developed algorithm was applied to the validation set images. Fig. 1 shows images at different processing steps. In Fig. 1b, the white circles are locations for potential green citrus fruit by CHT, and Fig. 1c shows initial detection result after circles with a smaller radius than the threshold was removed. Fig. 1d shows the step of removing false positives using SIFT. The symbols in the Fig. 1d are SIFT feature locations. Fig. 1e shows another removal step for false positives using the number of keypoints. Finally Fig. 1f shows the final recognition result.
FIGURE 1: Example steps for green citrus fruit identification

Table 1 below describes the results for both the sets in terms of total number of fruit, false positives and missed number of fruit. For this result, actual number of fruit was counted whenever the image showed 50% or more perimeter of a citrus, since it is not possible to detect a citrus whose perimeter is not visible by at least 50%.
There were three major challenges in green citrus detection: uneven illumination, partial occlusion, and color similarity. Uneven illumination was solved by implementing two separate tracks of algorithms for relatively brighter and darker images. Another major problem, partial occlusion, was tackled by adopting a low threshold value for the suitable parameter in the Hough circle detection module to include as many potential fruit as possible. However, sometimes due to the presence of shadow, it was almost impossible to detect partially occluded citrus fruit. Another challenge was to detect green citrus in presence of the green leaves, which are similar in color. Thus a more complex algorithm such as texture classification was utilized. Although the correct identification rate is high, there are also many false positives. Further research would be needed to increase the accuracy of correct identification, while lowering the number of false positives.

4. Conclusions
A novel approach was presented to detect green citrus fruit from images taken by a typical digital color camera under natural outdoor lighting conditions in the tree canopy. The approach utilized the circular Hough transform, texture classification with a support vector machine, and keypoints by scale invariant feature transform algorithm. Its performance was evaluated with a set of test images taken from a citrus grove. The Hough circle detection and texture classification based on SVM were implemented. Texture feature classification by SVM performed well in removing false positives. The results look promising, although further improvement would be needed.

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