POST-HARVEST QUALITY EVALUATION SYSTEM ON CONVEYOR BELT FOR MECHANICALLY HARVESTED CITRUS

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ABSTRACT

Recently, a machine vision technology has shown its popularity for automating visual inspection. Many studies proved that the machine vision system can successfully estimate external qualities of fruit as good as manual inspection. However, introducing mechanical harvesters to citrus industry caused the following year's yield loss due to the loss of immature young citrus. In this study, a machine vision system on a conveyor belt was developed to inspect mechanically harvested citrus fruit. Object based classification was conducted on RGB images acquired on the conveyor belt. Three ensemble learning classifiers AdaBoost, bagging and random forest, a relatively new method in machine learning, were trained with 74 features including color histogram features, textures and histogram intersection with immature and mature citrus color model. Overall performances of the three classifiers showed good classification ability for mature citrus (minimum 97% accuracy). Among them, the bagging trees showed the highest accuracy, 91.5, 89.1, 97.4, and 85.2% for green immature, intermediate, mature and diseased citrus, respectively.

Keywords: Automation, crop management, computer vision, image processing, precision agriculture.

INTRODUCTION

Grading of harvested fruit is important for screening its suitability for market place. An automated inspection reduces costs of production and increase accuracy of the process (Blasco et al. 2007). During the inspection, the citrus are sorted according to its size, weight, blemish and color. Recent studies have shown that an automated fruit inspection system using machine vision can effectively estimate its size, weight and quality as good as manual classification (Blasco et al. 2003; Leemans, 2002).

However, currently mechanical harvesters such as a trunk shaker and a canopy shaker have been introduced to the citrus production industry (Brown, 2005; Sanders, 2004; Whitney, 1999) and new challenges are encountered. In Florida, Valencia is one of major citrus varieties and its tree bears mature fruit as well as very young fruit for following year at the same time during a harvesting season. Consequently, the mechanical harvesters unavoidably remove immature fruit when they harvest mature fruit by shaking trees (Sanders, 2004). Therefore, a new approach to classify the mechanically harvested citrus has been required to identify maturity stages of fruit.

The maturity stages of the mechanically harvested citrus are categorized to four classes: mature, intermediate, diseased and small immature green fruit according to citrus' external qualities. The mature fruit shows yellow color in its surface dominantly (The Florida Legislature, 2010). Also, the intermediate fruit followed the definition of poorly colored citrus in United States standards for grades of Florida oranges and tangelos (USDA, 1997), that particularly represents the citrus that has solid dark green colors more than 25% in its surface. Furthermore, our research focused on the small immature green fruit that accidentally removed by the mechanical harvesters and the diseased fruit due to citrus Huanglongbing (HLB) and Melanose that cause skin discoloration.

Therefore, in this study, a machine vision system on a conveyor belt was developed to inspect the maturity stages of the mechanically harvested citrus: mature, intermediate, green and diseased. Image processing and classification algorithms were integrated to classify the harvested citrus based on surface color, size, and texture.

MATERIALS

Image acquisition on conveyer belt

A total of 82 images were used for experiments. The images were extracted from a video recorded on a conveyor belt (width: 34. 6 cm). A camera (Logitech C920, Newark, CA) was installed at 50.8 cm to record videos. The resolution of the video was 1920 by 1088 pixels and the field of view was 62.0 cm by 34.6 cm. The frame rate of the video was set to 30 frames per second. An external light was installed to provide sufficient illumination for video recording. An image contained citrus fruit harvested from an experimental citrus grove in University of Florida (Gainesville, Florida) on January 18th, 2014. Citrus were located on the rotating conveyor belt. Since the conveyor belt had a constant speed (51.6 cm/s) and the horizontal field of view is 62.0 cm, it took 1.2 second for a scene to pass the camera. The time needed to take a frame for a camera was 1/30 second/frame (0.033). Therefore, an image was extracted in every 36 frames (= 1.2 second/0.033 second/frame).

Fig. 1. An example of extracted images from a recorded video. The video was recorded using a camera (Logitech C920) on a moving conveyor belt.

Ground truth

A total of 92 images containing 385 citrus fruit were used. Among the 92 images, 75 images containing 306 citrus fruit were used for training and validation of the algorithm (3-fold validation) and 17 images containing 79 fruit were used to build color models of green immature and mature citrus fruit for calculating histogram intersection to measure color similarities (Cha, 2007). The 385 citrus in the images were classified and labeled manually into green, intermediate, mature and diseased fruit according to their maturity stages.

Table 1. Numbers of citrus fruit that used in the experiment.

	Training/Validation	Histogram model
Green	73	48
Intermediate	65	0
Mature	117	31
Diseased	53	0

METHODS

Image segmentation

There are two approaches for classification of an image: pixel-based classification and object-based classification. For the pixel-based classification, each pixel passes through a classifier to decide whether the pixel belongs to a region of interest (citrus in our experiment) or background. In this case, features that can be used for the classification are limited. Also, processing speed might be slow if a size of an image is large and containing millions pixels. On the other hand, the object-based classification considers a region of an image (a group of pixels) to decide if the region is the citrus or not. For this reason, the object-based classification can have an advantage that it uses extensive information such as texture, shape, size and color distributions. In our study, the object-based classification approach was used to identify the citrus from the background and its maturity stage. However, this approach requires image segmentation process prior to the classification to determine boundaries between different objects in an image.

In our algorithm, images were segmented based on contour of an object detected from gradient images of gray values. The high gradient values became edges of object. This method comes from an assumption that different objects have different colors so that the gradient values are higher near boundaries. However, citrus fruit that have the same maturity stage has similar color resulting in unclear boundaries between two objects when those are connected together. In order to fix this problem, one of well-known region based segmentation processes called a watershed algorithm using a flooding technique and h-minima transform were used in this study. The watershed algorithm uses topographic information of an image (Roerdink, 2001). For the topographic representation of the image, each pixel has a value of height that represents a distance from the nearest contour pixel of an object that the pixel belongs to. In each regional minima of the height values, it places a water source and starts flood from the water sources, and build barriers when different sources meets. Typically the watershed algorithm generates excessive segmentation due to excessive regional minima. The h-minima transform suppresses any regional minima that are smaller value than a threshold 'h'.

Maturity classification using ensemble learning

After the segmentation, a classifier was applied to detect citrus and decide its maturity stage. Three types of ensemble learning classifiers were used: 1) bagging (Breiman, 1996), 2) AdaBoost (Zhu, 2009) and 3) random forest (Breiman, 2001). The ensemble learning combines multiple classifiers to have a better result. In our study, a tree method was used as a classifier and multiple trees were combined to construct a strong ensemble classifier. The number of classifier to construct the classifiers was chosen from the training set to minimize misclassification rate. The three ensemble techniques, however, are different in ways of combining for each method. First of all, the AdaBoost combines classifiers by differentiating weights of each weak learner that are determined by iterations of training (Zhu, 2009). On the other hand, the bagging and random forest combine individual classifiers by averaging their results. The random forest limits the number of feature set that can be used during training the weak classifiers for generalization purposes (Breiman, 2001). A total of 73 features were measured including the number of pixels within detected citrus, diameters (long and short), four GLCM texture values in four directions (homogeneity, correlation, contrast and entropy), average and standard deviation values of normalized histograms in 13 color spaces of red, green and blue (RGB), hue, saturation and value (HSV), lightness, color opponents a and b (Lab), luminance, chrominance in red and blue (YCbCr) and gray scale. Also, histogram intersection values to measure similarities between detected citrus and green and mature color histogram models in the 13 color spaces were calculated in the 13 color spaces. To process the classification, a 3-fold validation method was used and an average of result from three sets was calculated to measure the classifiers' performance.

RESULTS

Image segmentation

In order to conduct the object-based classification, the acquired images were segmented before the classification. Firstly, original RGB color image was converted to gray level and the image gradient was obtained (Figure 2). In Figure 2, boundaries between objects that had different gray values were highlighted. Edges of the objects in the images were extracted using the gradient image and its complement image was used to segment objects (Figure 3).

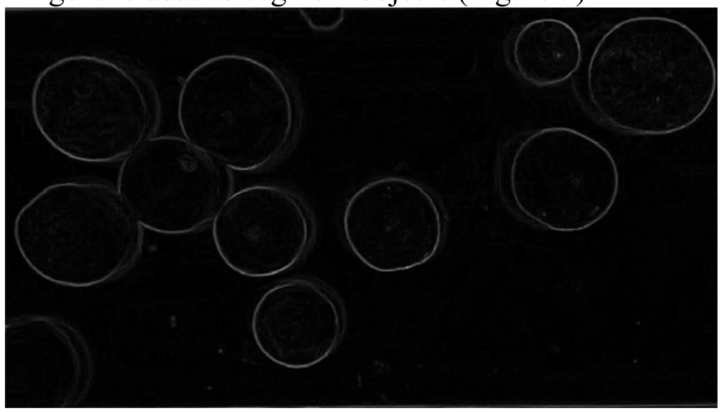

Fig. 2. A gradient image of the image shown in Fig. 1. Edges of object in the image were detected by calculating gradient values in gray level with neighboring pixels.

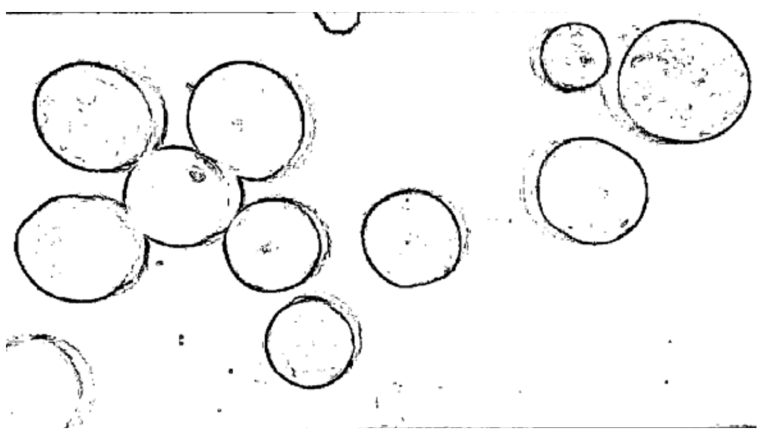

Fig. 3. A compliment image of the gradient image shown in Fig. 2.

To reduce processing time for watershed algorithm and classification, thresholding was conducted to remove backgrounds in advance. The threshold values were determined by color histograms of all five classes (background, green, intermediate, mature and diseased citrus). Two color components, gray and blue in RGB color space, were chosen since those two components had the largest variation between the background and the other citrus classes. The threshold values were 150 in gray level and 70 in blue component. After the thresholding, most of the background was removed as shown in Figure 5. However, there were still remaining background and these were passed to the classifier to decide whether it belongs to the citrus or the background. After the thresholding, holes inside of objects were filled (Figure 5).

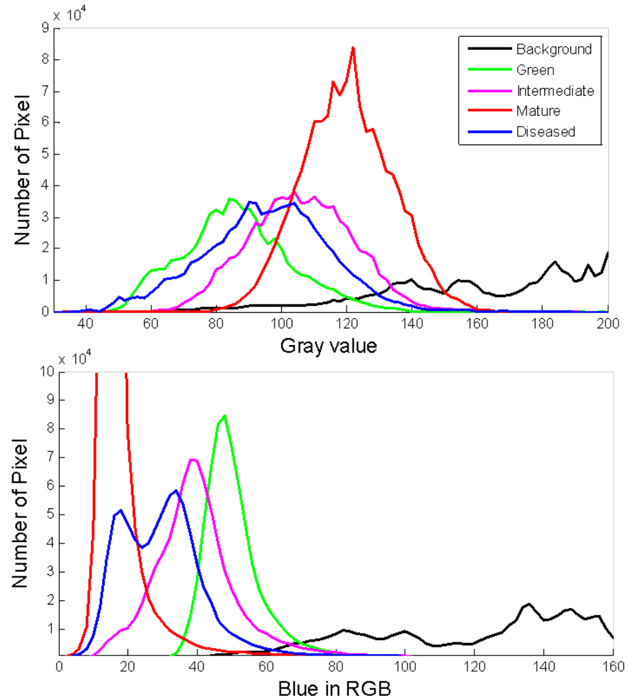

Fig. 4. Histograms of gray and blue components in RGB color space. The values of threshold were chosen to be 150 in gray and 70 in blue to remove the background.

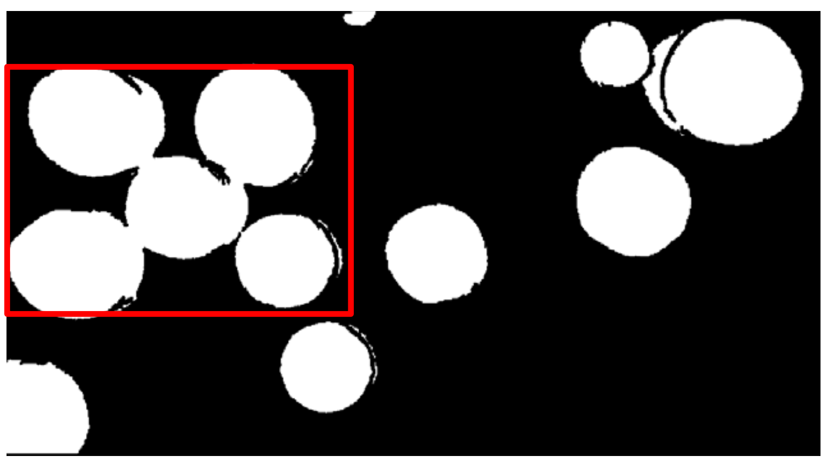

Fig. 5. A result image after thresholding to remove background pixels and filling holes within objects.

In order to process the object based classification, every object in the image should be segmented separately. However, in Figure 5, five citrus fruits in a red box were connected each other. These connected fruit would cause a problem since connected objects were considered as one object during the classification. Therefore, the watershed algorithm with h-minima transform was performed. The value of ‘h’ was decided to be 8 by trials and errors using the images that were acquired additionally.

A result image of applying the watershed algorithm with h-minima transform is shown in Figure 6. Inside of the red box in Figure 6, connected citrus were separated successfully. A zoomed view of the red box after the watershed algorithm is shown in Figure 7.

Fig. 7. Zoomed view of the image within red box in after the watershed algorithm with h-minima transform (h=8). 4. Connected citrus objects were separated successfully.

Table 2 shows the final result after the image segmentation. In the images, a total of 398 objects were found (ground truth) including 90 background, 73 green, 65 intermediate, 117 mature and 53 diseased citrus. After the segmentation, the most of the citrus and background were separated well except two missed green citrus and one overly segmented diseased citrus.

Table 2. Result of the image segmentation process.

	Total number of object	Correctly segmented object	Overly segmented object	Missed object
Green	73	71	0	2
Intermediate	65	65	0	0
Mature	117	117	0	0
Diseased	53	52	1	0
Background	90	90	-	-
Total	398	395	1	2

Maturity classification using ensemble learning

After the segmentation, the classification was performed to decide whether the segmented objects belonged to the background or citrus. Additionally, if the object was classified as a citrus, its maturity stage was decided as well. Table 3 shows the classification result of the three ensemble learning classifiers: the AdaBoost, bagging and random forest. To train classifiers, 220, 180 and 180 trees were combined to construct the Adaboost, bagging and random forest classifiers, respectively. The performance of each classifier was analyzed by correct identification rate. The values of the correct identification in the Table 3 are the average of three sets in the 3-fold validation. Overall performances of three classifiers were good for the classification of the background and mature citrus. However, the AdaBoost classifier showed relatively poorer performances for classifying the green, intermediate and diseased citrus.

Table 3. Results of the maturity classification in terms of correct classification using a 3-fold validation method. The correct identification rate is an average value of the three sets. (Unit: Number of object and percent in parenthesis).

		Remained Back-ground	Green	Inter-mediate	Mature	Disease
	Total	90.0	71.0	65.0	117	54.0
	Average	30	23.7	21.7	39.0	18.0
Adaboost	Correct identification (%)	29.3 (97.8)	18.7 (79.0)	17 (78.5)	38 (97.4)	1.3 (7.4)
Bagging	Correct identification (%)	29.7 (98.9)	21.7 (91.5)	19.3 (89.1)	38.0 (97.4)	15.3 (85.2)
Random Forest	Correct identification (%)	29.7 (98.9)	21.7 (91.5)	18.6 (86.2)	38.3 (98.3)	15.3 (85.2)

DISCUSSION

The results from the image segmentation showed two missed fruit and one over-segmented fruit. The two missed fruit were green citrus smaller than those in other maturity stages. The small size of the citrus caused relatively lower gradient values during the edge detection that caused to fail to detect edges of the green citrus. For the overly segmented citrus, the diseased fruit had a linear pattern inside of the citrus that caused another edge within the object. Additional edges inside of the object caused over-segmentation since edges were considered as boundaries between different objects.

For the maturity classification, the AdaBoost classifier had the lowest accuracy since the classifier used only one feature with three nodes when constructing a tree classifier. The diseased and green citrus had complex characteristics in color and texture, so it was hard to classify with only one feature.

CONCLUSION

A machine vision system on a conveyor belt to estimate maturity stage of citrus was developed. Object based classification with three ensemble learning techniques, AdaBoost, bagging and random forest, were used to develop machine learning algorithm. A total of 73 features including average and standard deviation of histogram in 13 color spaces, four GLCM texture and histogram intersection with green and mature citrus color model were analyzed according to its maturity stage of citrus.

Correct identification rate of bagging and random forest classifiers were high for all maturity stage citrus, especially, the bagging classifier performed best among three classifiers.

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