Identification of red apples in field environment with over the row machine vision system

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Abstract: Accurate detection and identification of fruits is critically important for the success of developing automated apple harvesting system. Research has been conducted to identify apples in orchard environment with reasonable accuracy when apples are clearly visible or partially occluded. However, only limited work has been carried out to identify fruit in clusters, which is critically important as fruit clusters are common in field conditions. This work focused on accurately identifying partially visible apples and apples in clusters using a machine vision system. An over the row platform with tunnel structure and artificial lighting was used to increase uniformity in imaging environment. Iterative Circular Hough Transform (CHT) was used to detect clearly visible fruit as well as individual fruit in cluster. Partially occluded apples were detected using blob analysis; a clustering algorithm based on Euclidean distance between centroids of blobs was used to merge the parts of an apple divided by occlusion. Potential fruit detected by CHT and blob analysis were passed through a color identification process to decide if they were apples. This algorithm was successfully tested with 60 images of apple trees and resulted with 90% apple identification accuracy. On average, CHT detected 54% of total identified apples whereas blob analysis detected remaining 46% with overall false positive of 1.8% and false negative of 8.2%. The fusion of blob analysis and CHT significantly increased detection accuracy compared to individual methods exclusively including that in clusters. The results showed potential for in-field apple identification for automated apple harvesting.

Keywords: Apple identification, clustering, Circular Hough Transform, blob analysis

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1 Introduction

Research and development in robotic tree fruit harvesting has been a major focus in recent years because of decreasing supply and increasing cost of human labor. One of the major tasks of a fruit harvesting robot is to identify or detect fruit in tree canopies (Bulanon et al., 2002; Baeten et al., 2008). Machine vision-based fruit identification is also important for accurate crop-load estimation for crops such as apple and citrus.

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Researchers have implemented machine vision systems in various ways to automate fruit identification. Tabb et al. (2006) developed a method of Global Mixture of Gaussians (GMOG) based on the principles of Mixture of Gaussians (MOG). The method resulted in an identification accuracy of 85% - 96% for both red and yellow apples. Stajnko et al. (2009) used color and texture segmentation followed by Circular Hough Transform (CHT) and reported an accuracy of 89% on identifying apples in canopy images acquired in outdoor environment. Inspired by Eigenface algorithm (Sirovich and Kirby, 1987), Kurtulmus et al. (2011) used Eigenfruit approach using color intensity and saturation along with circular Gabor texture to identify green citrus fruit. Ji et al. (2012) investigated an image segmentation method based on region growing and color feature to separate red apples from rest of the image. Image segmentation for fruit identification has also been investigated with the use of texture properties in addition to color and geometric properties (Stajnko et al., 2009, Hannan and Burks, 2004, Linker et al., 2012). Linker et al. (2012) used color and smoothness to form and extend seed areas to generate a simple model of apple and achieved 85% accuracy on identifying green apples. Payne et al. (2013) used texture filters including Hessian filter to remove leaves, trunks and stems in identifying mangos. Supervised classification based on soft-computing methods such as Support Vector Machine (SVM) (Wang et al., 2009; Moonrinta et al., 2010; Rakun et al., 2011), and Artificial Neural Network (ANN) (Huang et al., 2010) have also been used in the past to identify fruit in tree canopy images. However, most of these researchers observed that variable lighting condition, clustering and occlusion pose challenges for accurate fruit identification in orchard environment (Plebe and Grasso, 2001; Hannan and Burks, 2004; Zhao et al., 2005; Stajnko et al., 2009; Rakun et al., 2011; Kurtulmus et al., 2011; Linker et al., 2012; Ji et al., 2012).

To address the issue with fruit clustering, Zhao et al. (2005) developed a method to separate connected apples in binary image using texture based edge detection. Later necking region in the contour was used to split apples in clusters. Although, this approach efficiently split both red and green apples in clusters with minor overlapping regions, performance of such system under high clustering is not known. There is still a need for developing robust methods that can detect individual fruit in highly clustered conditions commonly occurred in apple or other tree fruit orchards.

Lighting condition is another important factor that needs to be considered in outdoor machine vision as it has direct impact on the robustness of fruit identification methods. Tree canopy images captured under direct sunlight lack uniformity of illumination and may be saturated with color information (Kurtulmus et al., 2011; Linker et al., 2012). Non-uniform light intensity induces fruit identification errors due to coexistence of bright spots and shadows, and alteration of color and texture in images (Jimenez et al., 2000; Stajnko et al., 2004; Stajnko el al., 2009; Kurtulmus et al., 2011). To minimize the effect of direct sunlight, Linker et al. (2012) acquired pictures after sunset. Ji et al. (2012) investigated the potential of underexposure of sensor and image acquisition under diffused lighting condition and reported that identification accuracy can be increased to 95% with false positive less than 5%. Wang et al. (2013) evaluated an image acquisition system at nighttime with controlled artificial lighting and reported a consistent illumination in images. However, such approaches may be limiting in applications to crop-load estimation and fruit harvesting as imaging could be conducted only at a specific time. Design of a physical shading structure with controlled artificial lighting system to control the lighting on the canopy during day and night would provide a uniform environment for image acquisition and greatly minimize these issues.

In this research, challenges of fruits in clusters, partial visibility, and variable lighting condition in apple identification were addressed. An over-the-row sensing system with a tunnel structure was designed to create a semi-controlled lighting environment to enhance illumination uniformly. The specific objective of this research was to develop a machine vision system for accurately identifying individual apples in color images captured under a semi-controlled artificial lighting environment.

2 Materials and methods

2.1 Imaging platform and data collection

An over the row platform with a tunnel structure was designed to provide a uniform environment for imaging. An opaque curtain secured around the platform blocked direct sunlight onto the tree canopy (Figure 1), which helped acquire images with minimal specular reflection. A semi-controlled lighting environment was created within the platform using a set of white LED lights

(Trilliant® 36 Light Emitting Diodes Grote, Madison, Indiana) for day and night time operations (Gongal et al., 2014; Gongal 2014). However, for this study images were captured only at daytime.

Figure 1 Over the row sensor platform used to acquire images of apple trees in commercial orchards in Grandview, WA and Prosser, WA (Gongal et al., 2014)

The platform was mounted on a tractor and moved in-between orchard rows for acquiring images of different trees as shown in Figure 1. The camera was placed at the center of longitudinal section of the sensing platform and images were taken from various locations along the vertical axis to cover entire trees. Static color images were acquired using Prosilica GigeE 1290C from Allied Vision Technology. This Charged Coupled Device (CCD) camera used f1.4/6 mm lense with 43.6˚ (horizontal) by 33.4˚ (vertical) Field of View (FOV) and 1280 × 960 image resolution. On average the camera was roughly 1 meter away from apples. In general, major axis of the apples used in this work varied from 6 to 8 cm. Minor axis was slightly smaller but we assumed apples to be circular in images. With 43.6˚×33.4˚ FOV and 1 m average distance from camera to apple, size of apples in images varied approximately from 35 to 70 pixels. Images of Jazz and Fuji apple trees were acquired in tall spindle orchard architecture (row spacing 2.74 m and inter-plant spacing1.17 m) in Prosser and Grandview, WA (Allan Bros., Inc., Naches, WA). Images were captured during 2013 harvest seasons in WA. The proposed machine vision algorithm was tested over 60 images of apple trees acquired with over-the-row platform.

2.2 Image processing for apple identification

An image processing algorithm was developed and tested with 60 color images captured in commercial apple orchards. Figure 2 is the generalized block diagram of the proposed image processing algorithm. Initially, the color of all images was equalized in Hue, Saturation, Intensity (HSI) color space, which provided more contrast between apples (red color) in foreground and green leaves and other colors in the background. Binary images were obtained by subtracting green and blue channels from red channel in RGB color space. Then, CHT was used iteratively to find circular objects of varying size. Fragments of apples with irregular shapes were identified using blob analysis. A clustering algorithm was then used to merge fragmented parts of the same apple to

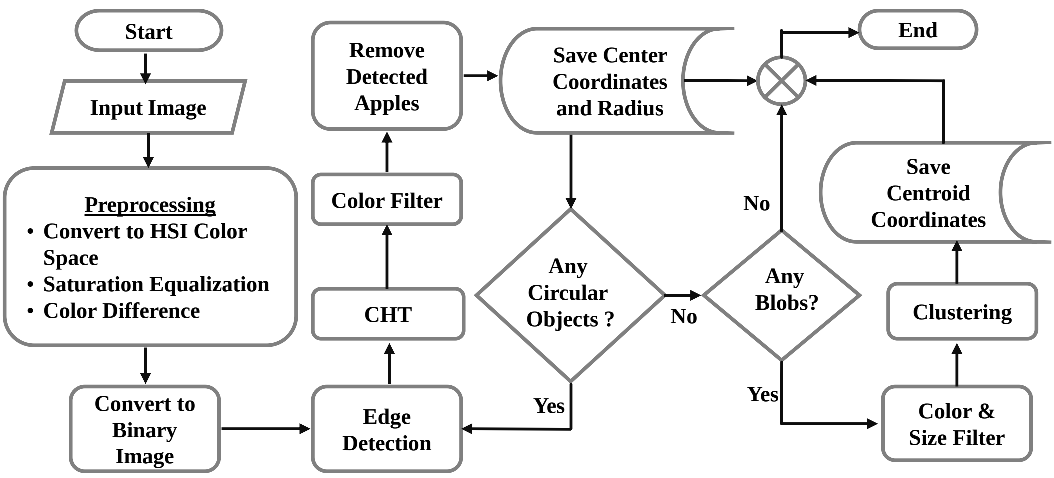


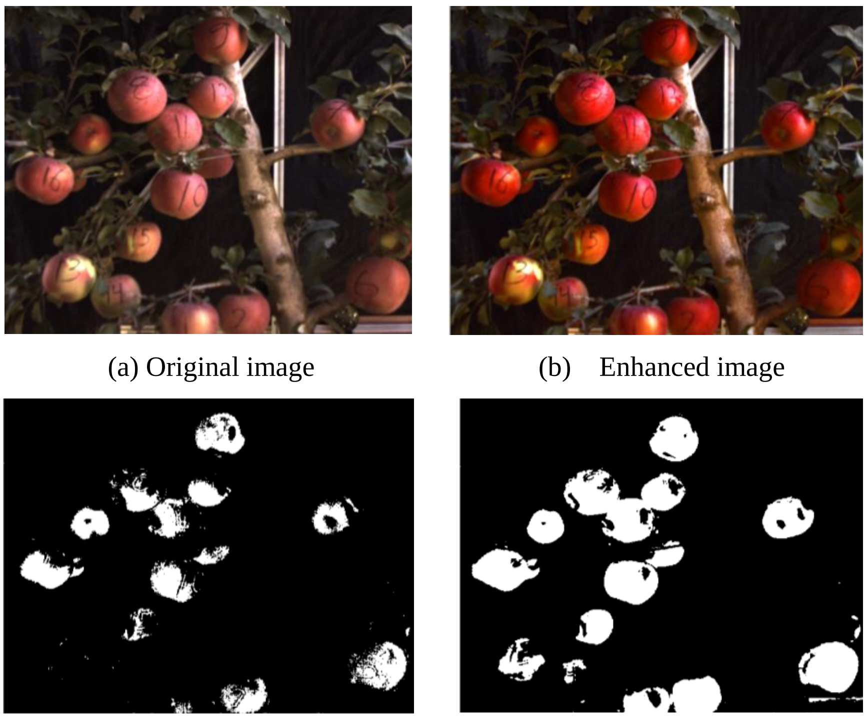
Figure 2 Block diagram of proposed machine vision algorithm

minimize multiple detection of the same apple. Finally, the results of CHT and blob analysis were fused together to improve the accuracy of apple identification. These steps will be explained in the following sub-sections.

2.2.1 Image preprocessing

The accuracy of the apple identification algorithm greatly depended on the uniformity of edges of apple surfaces in the image. To improve the uniformity of edges, purity of color of entire images were enhanced using saturation equalization technique in HSI color domain. As a consequence of equalization, color difference between red apples (foreground) and green leaves and branches (background) was intensified leading to higher contrast between foreground and background. However, this operation also had the tendency to increase noise. To suppress such induced noise; a pixel wise adaptive Wiener filter of neighborhood size of 5×5 was implemented. Wiener filter was selected for this purpose as it provided an optimal way of tapering off the noisy components (Gonzalez et al. 2010). Next, images were converted back to RGB color space for segmentation. Segmentation of apples from background was carried out by subtracting both green and blue channels from red channel (Gray = R-G-B). This algebraic operation filtered apples from leaves and branches while maintaining the spatial characteristic of the image even though some pixels were negative and other were positive. The resulted grayscale image was then converted into binary image using Otsu's global image threshold method (Gonzalez et al. 2010), which determines the optimal threshold value for separating pixels in images into foreground and background classes with minimum intra class variance. Canny edge detector was used to extract the edge information because of its ability to detect weak edges using two separate thresholds for detecting weak and strong edges (Gonzalez et al., 2010).

Figure 3 represents an example image showing the effectiveness of the image enhancement technique used in this work. Saturation equalization and adaptive filtering of original image (Figure 3a) resulted in the enhanced image as shown in Figure 3 (b). Compared to the image without enhancements (Figure 3c), this technique generated high level of contrast between foreground and background with prominent edge information (Figure 3d). Image enhancement helped identify those apples which



(a) Original image (b) Enhanced image

(c) Binary image without enhancement (d) Binary image after enhancement

Figure 3 Binary images with and without saturation equalization obtained using Otsu's method.

would otherwise be lost in the background during segmentation.

2.2.2 Apple identification approach

Qualitative observation of images taken during field data collection revealed that visibility of apples varied widely; some were clearly visible and separated from others by considerable distance whereas others located very close to each other forming clusters. The images also included apples with varying degrees of occlusion by leaves, branches and other apples adding difficulties to apple detection. To address these issues of varying level of complexity, a two-tier approach of apple detection was used: CHT followed by Blob Analysis.

Iterative CHT: First, CHT was applied to detect apples in relatively simpler scenario, which included clearly visible apples in individual or clustered environment. As the size of apple as well as the distance to apples from camera varied based on the position of apples in tree canopies, the size of apples in images also varied from about 35 pixels to about 70 pixels. CHT was implemented to search for objects with circular boundaries, thus it was necessary to define a range for search space to minimize computation time. Minimum (35 pixel) and maximum (70 pixel) radius of apples in images were manually estimated using a randomly selected image. The lower limit of the radius was also necessary to eliminate detection of small circular areas (less than 100 pixel size) as apples. CHT used the edges generated by Canny edge detector and circles of predefined radius were drawn over each edge pixel. The pixel value in the accumulator through which circles were drawn was incremented each time a circle was drawn. Edges with circular shapes had more intersection within circles compared to non-circular edges. These inter-circular intersections gave rise to peaks in the accumulator space indicating presence of circular object. This way CHT incorporated both shape and size information and application of such technique over boundary pixel emanated several peaks as candidates for circular objects in Hough's accumulator.

A threshold of minimum number of votes in the accumulator and a predefined separation distance between maxima were used to suppress unwanted maxima. However, such suppression approach had limited benefit as a fixed threshold was not appropriate for different images and occasionally did not detect all apples that were in close proximity of each other. This limitation was addressed using an iterative approach where different thresholds were introduced over different iterations. Appropriate thresholds were selected manually on trial and error basis. Coordinates of the centers and radius of the detected objects were used to remove previously detected apples before a new iteration so that duplicate apple detection could be avoided. Such removal of previously identified apples and multiple thresholding allowed initially suppressed maxima's to reappear again in next iteration for detection. The iterative CHT was continued until no maxima appeared in the accumulator.

As edges of apples were not completely circular, CHT sometimes generated multiple circles within and around a single apple. These unwanted circles had centers or peaks that were very close to each other in the accumulator which generated multiple detections for single fruit. Likewise, presence of highly overlapped apple in an image had similar effects where two or more apple centers were present very close to each other. Such cases created confusion in deciding if the presence of multiple peaks were from single fruit or overlapped multiple fruits, which sometimes led to false negatives in apple identification.

Blob Analysis: CHT detected majority of apples, but partially visible apples due to occlusion were not detectable with such approach. To detect remaining apples after CHT, a blob analysis method was used. In this analysis, area and perimeter were estimated to calculate object compactness, which served as a function for deciding if a fragmented blob belonged to an apple. Only those blobs that had area and compactness above minimum threshold (100 pixel size) were considered as part of apple. Conversion of images with partially occluded apple into binary images resulted in multiple fragments for single fruit, which had irregular shapes and complex appearance. To avoid multiple detection of the same apple, individual fragments of an apple in the image were merged together using Euclidian distance between centers of blobs. This merging approach included iterative searching of blobs within close vicinity. The searching method was started with labeling blob individually, which helped identify each of the blobs uniquely. Then a circle of radius equal to upper limit of apple radius as used in CHT was drawn about the centroid of the first blob. If the centroids of other blobs were within the circumference of this circle, they were merged and considered as part of same apple. This process was repeated to other remaining blobs until no centroid appeared within the search radius.

2.2.3 Object filtering with color

The objects of interests detected by CHT and blob analysis were subjected to a color detection process. Although, segmentation of apples was based on color information, the image segmentation was not perfect leading to some branches, parts of trunk or dry leaves being falsely detected as apples, especially with blob analysis when shape information was not available. A final step of red color detection was used to remove falsely identified apples that would have similar Gray (R-G-B) information (used in the original segmentation) but low intensity in Red channel. RGB color space was chosen because of its inherent simplistic nature. First, RGB pixel components of each object detected from CHT and Blob Analysis were transformed into normalized value using the following equations.

$$r = \frac{R}{R+G+B}, g = \frac{G}{R+G+B}, b = \frac{B}{R+G+B}; r + g + b = 1$$

Where, r, g and b are the normalized value of each RGB pixel in images.

This transformation removed the intensity information, reduced the color space to two dimensions as the relationship between the variable became linearly dependent (Stajnko et al., 2004). A threshold value of r, g and b chromatic coordinates was determined by calculating average values of red, green and blue channels of apples from 60 different images. The average value of normalized coordinates of the objects with circular feature detected by CHT and blobs detected with Blob Analysis were required to be above the calculated threshold to qualify as an apple.

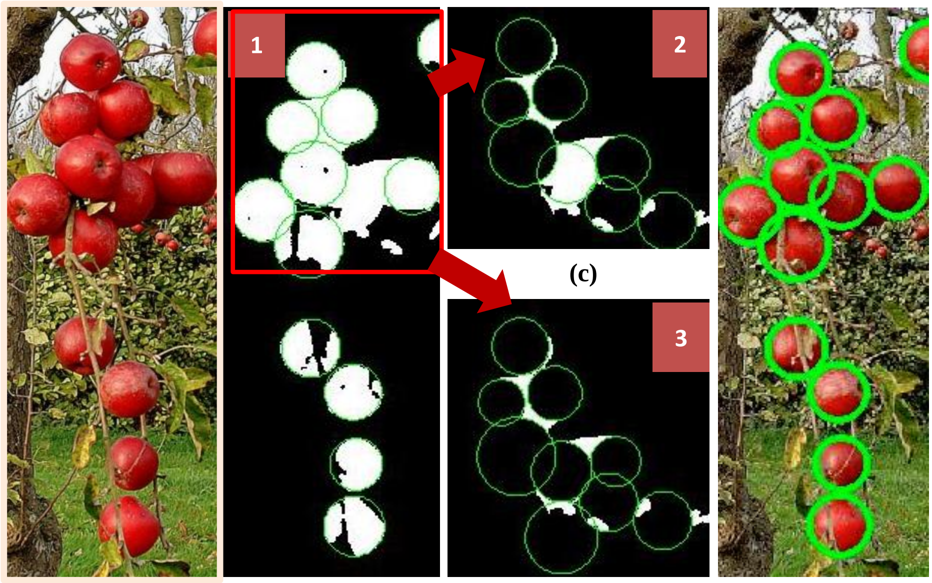
In this work, accuracy was defined as closeness of number of apples identified by the algorithm to manually counted apples in images. Total error was interpreted as misclassification or algorithm's inability to identify apples. Circular objects and blobs detected by machine vision system as apples but were not actual apples or parts of it were defined as false positives. On the other hand, apples that the algorithm was not able to identify contributed to false negative error.

The proposed Machine Vision algorithm was implemented in MATLAB software (R2012b, Mathworks Inc.).

3 Results and discussion

3.1 Apple detection using CHT

During algorithm development phase, CHT was tested over images from different sources including left-most image in Figure 4 with a lot of clustering (WilderUtopia, 2014). Result of CHT over three iterations are portrayed in Figure 4 (b,c,d) labeled as '1, 2 and 3'. Most of the apples were detected in the first iteration marked by circles in Figure 4(b). The empty circles in Figure 4(c) and 4(d) resembles the removed apples that were detected in previous iterations. Subsequent iterations of CHT resulted in accurate identification of individual apples even in heavily clustered regions of apple canopy images.

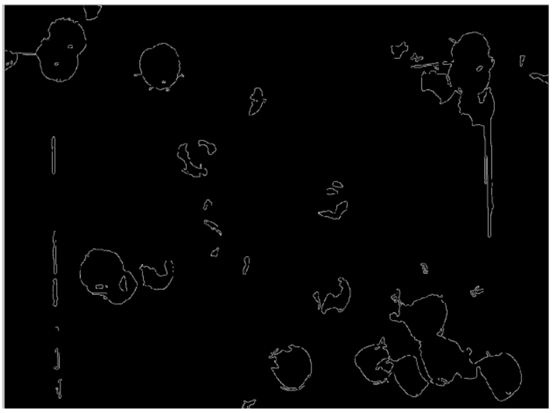


(a) (b) (d) (e)

Figure (a) depicts the input image, whereas first iteration with CHT is depected in (b), second iteration of only upper part of image is shown in (c), and third iteration with no circular objects is shown in (d). Final result after three iterations is shown in (e)

Figure 4 Apple detection in a heavily occluded environment with multiple iterations of CHT

Iterative CHT algorithm was then applied to apple canopy images captured in commercial orchards in WA. The algorithm was able to detect most of the apples with prominent circular edges. Because image enhancement technique was able to preserve most of the edges, individual apples in clusters were accurately detected in most of the cases as seen in corners of the image in Figure 5. Some false negatives occurred mostly when apples were highly occluded by another apple as in the case of the top left corner of the image where only two apples were identified out of three in the cluster. Such false negatives were caused because of the limitation set in CHT to discard apples within extreme proximity. Comprehensive accuracy assessment was carried out after results from CHT and blob analysis were combined as discussed in section 3.3.



(a)

(b)

Figure 5 Edges of the objects in a apple canopy image (a), and detection of potential apple regions with CHT (b)

3.2 Apple detection using Blob Analysis

Occlusion from branches and leaves compromised the shape integrity of apples and resulted with multiple fragments of the fruit in binary image (Figure 6). The result of blob analysis and clustering algorithm has been depicted in Figure 6 where blobs were identified as parts of apples using color and size information and clustering algorithm merged the fragmented parts of individual apples.

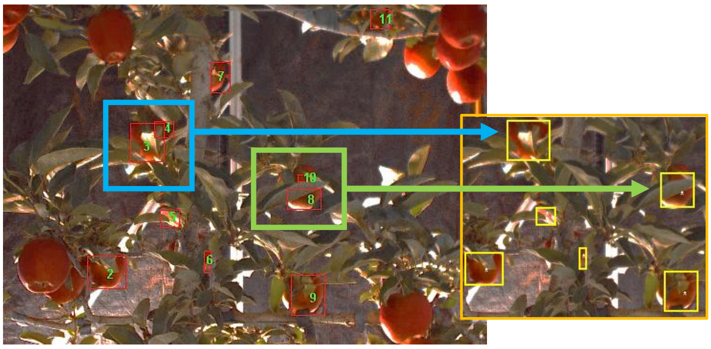


Figure 6 Fragments of the same apple merged together using a clustering method as represented by smaller boxes in the right image.

3.3 Accuracy assessment and discussion

The combination of CHT and blob analysis approaches was tested over 60 different images of apple trees acquired in two different commercial orchards. Figure 7 shows the final result of this algorithm after fusing CHT and blob analysis. This fusion resulted in 90% accuracy in identifying apples with overall false positive of 1.8% and false negative of 8.2%. On average, CHT detected 54% of apples whereas blob analysis detected the remaining 46% of the total successful detection. A PC configured with Intel Core 2 Quad processor at 2.66 GHz clock rate, 4 GB RAM and windows 7 64-bit Operation System was used for processing the machine vision algorithm and calculation time per image was approximately 7 seconds. Because the major goal of this work was to evaluate the accuracy of apple identification algorithm, optimizing computational speed was outside the scope of this work. As the algorithm was implemented in Matlab environment without any optimization, it is expected that a substantial improvement in computational speed may be possible with optimization of code and programming platform, as well as hardware and software architectures.

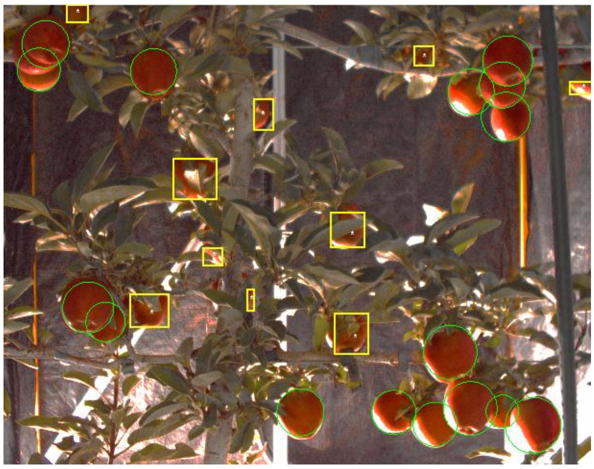


Figure 7 Example of apple identification result generated by the fusion of CHT (circles) and blob analysis (rectangles) respectively

The linear regression plot (Figure 8) between manual and automated count of apples yielded R^2 value of 0.96 showing a close proximity between algorithm and actual values. The root mean square error between manual and automated count was 2.67. It is also noted, however, that some images with large number of apples suffered from substantial number of false negatives, caused primarily by a high degree of clustering and occlusion. Dense population of apples in these trees caused multiple overlapping of fruit making them only minimally visible in many cases and enforcing the algorithm to undermined detection of closely located apples with CHT. Furthermore, segmentation of images in such a complex senario resulted in images with multiple fragments of different apples located close to each other. The clustering algorithm based on Euclidean distance in these extreme cases clustrered parts of different apples together within a close vicinity increasing the number of false negative identification (Table 1). Although the sensor platform had semi-controlled lighting environment, under dense apple population some fruit were under shadows from branches, leaves and clusters of apples. The presence of shadow made the fruits less visible, and changed its color; as a result some fruit were lost during segmentation or color filtering process. These circumstances contributed to higher false negative and therefore reduced detection accuracy.

Table 1 Confusion matrix for apple identification

		Predicted		
		Apples	Not apples	False negative
Actual	Apples	**978**	**88**	**8.2%**
	Not apples	**18**		
	False positive	**1.8%**		

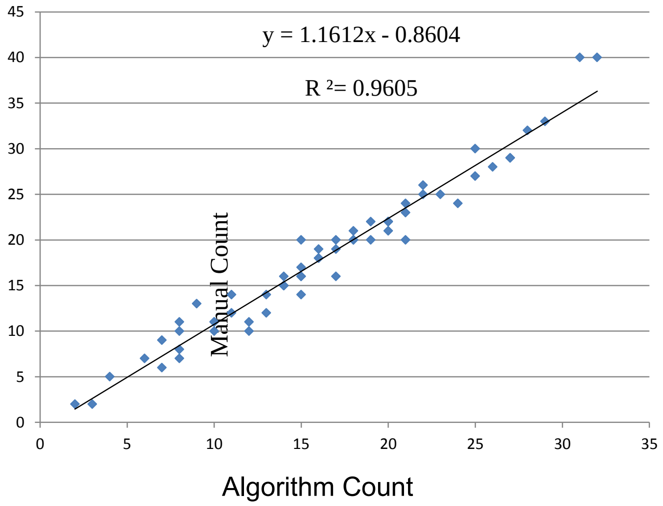


Figure 8 Linear regression between algorithm and manual count

After data collection it was realized that a few images had objects in background with color information close to that of apples (e.g. wooden structure supporting the sensor platform). This situation added a challenge in finding appropriate threshold value that would work for entire dataset. Non-green leaves with circular edges also caused some issues. Image segmentation did not completely filter out these leaves and wooden structures, which were sometimes identified as apples because threshold color separation did not robustly ignore them. Further work on training, pruning and thinning approaches of apple trees to improve visibility and reduce clusters would help improve overall apple identification accuracy. When this method is used in apple harvesting, the issue of false negative can be addressed by applying identification method repeatedly as the harvesting operation progresses. As clearly visible apples are harvested, visibility of remaining apples will improve, providing better opportunities for accurately identifying more apples.

Furthermore, a hybrid system of human machine collaboration could be added where human would apply minimal efforts in identifying apples at places difficult for computer to identify. High accuracy and robustness could be anticipated from such a collaborative system. In this work, images were taken with a stationary platform. Further work would be necessary to improve the stability of the sensing platform and to integrate an image stitching method so that this technique could be applicable for real-time operation in the field.

4 Conclusions

A machine vision system with artificial illumination to identify red apples in RGB images was developed with an emphasis to improve detection in outdoor environment and when apples were in clusters. A fusion of Circular Hough Transform (CHT) and blob analysis with clustering algorithm was used to identify apples in the images captured using an over-the-row sensor platform. The system used a set of artifical lights under a tunnel structure and provided an opportunity to accurately identify apples during day-time operation.

The over-the-row sensing system based machine vision system developed in this work showed a promise for accurate apple identification in outdoor environment. On average, the method achieved an identification accuracy of 90% with a false positive of only 1.8% and false negative of 8.2%. The method was also robust as a reasonably high accuracy was achieved with an unsupervised method tested over 60 canopy images of two apple varieties captured in daytime using an artificial light. To minimize false negative and further improve apple identification accuracy, images could be captured from two or more sides of tree canopies. This research served as a prelude to integrating 2D and 3D imaging for identification and localization of apples for accurate crop-load estimation and automated harvesting. Inverse mapping of 2D image to 3D information would minimize the repetitive count of apples visible in images acquired from multiple camera locations and provide 3D locations required for harvesting and for size estimation of identified fruits.

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