Apple detection from apple tree image based on BP neural network and Hough transform

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Abstract: Using machine vision to accurately identify apple number on the tree is becoming the key supporting technology for orchard precision production management. For adapting to the complexity of the field environment in various detection situations, such as illumination changes, color variation, fruit overlap, and branches and leaves shading, a robust algorithm for detecting and counting apples based on their color and shape modes was proposed. Firstly, BP (back propagation) neural network was used to train apple color identification model. Accordingly the irrelevant background was removed by using the trained neural network model and the image only containing the apple color pixels was acquired. Then apple edge detection was carried out after morphological operations on the obtained image. Finally, the image was processed by using circle Hough transform algorithm, and apples were located with the help of calculating the center coordinates of each apple edge circle. The validation experimental results showed that the correlation coefficient of R^2 between the proposed approaches based counting and manually counting reached 0.985. It illustrated that the proposed algorithm could be used to detect and count apples from apple trees' images taken in field environment with a high precision and strong anti-jamming feature.

Keywords: apple detecting and counting, BP neural network, Hough transform,color segmentation, edge detection

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1 Introduction

It is important to estimate fruit yield in apple orchard precision production management, and that is a key supporting technology to study the apple and apple tree growth rhythm quantitatively. Accurate yield estimation can effectively help farmers to improve fruit quality through reasonable pruning and reduce labor costs by designing planting and harvest plan. The typical yield estimation method is usually conducted based on historical data and weather conditions, and manually sampling statistics is also frequently used. However these methods are all time-consuming and their prediction results are not accurate enough. Moreover, precision orchard production management cannot be carried out since the estimation results do not show fruit yield distribution in orchard, especially in a large orchard with high spatial variability. Therefore, an automated orchard yield estimation method is necessary for the development of modern precision orchard.

With the development of information technology, machine vision based measurement method has shown great potential to replace manual methods when estimating apple yield. Some agencies have developed a variety of machine vision based detection and counting systems. Wang et al.[1] developed a computer vision based system for automated, rapid and accurate apple

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yield estimation. The system used two camera stereo rigs for image acquisition, and the results showed that the system worked well with both red and green apples. However, the system must be used with controlled artificial lighting at nighttime, and its software has a limitation in dealing with fruit clusters comprised of more than two apples. Payne et al.[2] proposed a machine vision based approach to count the number of mango fruit from daytime images on individual tree for estimating of mango yield. In which, pixels were segmented into fruit area and background using color segmentation in the RGB and YCbCr color spaces with threshold methods and texture segmentation according to adjacent pixel variability. Then the number of fruits was obtained by counting the number of specific connectivity regions. However, this method did not consider the circumstances of overlapping and covering. Zhou et al.[3] developed an apple fruit recognition algorithm based on color features which were the difference of R-B (red minus blue) and G-R (green minus red) to estimate the number of fruits. However, this method was not well adapted to changes of illumination and shading problems among fruits, branches and leaves. Accordingly the final result was not clearly visually displayed. Nuske et al.[4] presented an automated method that used computer vision to detect and count grape berries. They used both shape and visual texture features to detect berry and demonstrated segmentation of green berries from green leaves. However, since a radial symmetry transform was used to find the grape center points, it led to a large amount of arithmetic operation, and resulted in difficult application. Hung et al.[5] proposed a multi-class image segmentation approach to automate fruit segmentation without pre-defined features descriptors. A feature learning algorithm combined with a conditional random field was applied to process multi-spectral image data and its global accuracy was 88%. However, it did not incorporate the concept of objects so that it could not provide the actual fruit count and run in real time with 5 s per image processing. Other fruit yield estimation studies based on machine vision also cannot provide reliable results[6]. Crop yield estimation by using digital camera acquired images has been practiced for crops such as wheat[7], wild blueberry[8] and rice[9]. It has advantages of low cost, short operation time and easy management from the ground[10]. However, it is necessary to develop a fast algorithm for apple yield estimation using RGB ground images which are more convenient for farmers to acquire. The algorithm should have a strong robustness in detecting and counting apples even in the circumstances such as illumination changing, partially covered by leaves and branches, overlapped by other apples, complex background and other issues under natural light and field conditions which are shown in Figure 1.

a. Illumination uneven and sheltered by leaves

b. Apple sheltered by branches

c. Apple overlapped

d. Apple color variation

Figure 1 Apple pictures under natural conditions

To develop a mature and stable fruit yield estimation algorithm, several key issues have to be solved in order to realize fruit detecting and counting precisely. Under natural light and yield conditions, the following four questions are faced when using machine vision technology:

1) Changing in illumination: Changing of illumination causes color changes of the fruit images (Figures 1a and 1d), and it has a great effect on the recognition algorithms based on color features. Thus fruit recognition algorithm has to be designed not to be affected by light, and this is the premise to build a stable apple recognizing and counting system.

2) Shading: Apples may be partially covered by leaves and branches, and thus it is difficult to detect the full area of the fruit (Figure 1a), and fruit pixel area may be divided into pieces (Figure 1b).

3) Overlapping: Fruit overlapping occurs when the positions of fruits are too close (Figure 1c), in this case, the apples may be detected as one apple pixel region

mistakenly. Thus apple counting algorithm needs to separate this pixel region into actual different individual fruit regions to get the accurate fruit counts.

4) Fruit color variability: Because of individual apple differences in color, fruit detection algorithm has to adapt to normal changes in color (Figure 1d).

In this study, in order to meet the actual demand of apple yield estimation, a color and shape feature model based algorithm was proposed to detect and count apples on apple tree images. It aimed at developing an algorithm that could focus on solving the above four problems to achieve accurate apple detecting and counting from fruit tree images. In RGB color space, because apple color distributes irregularly for the reason of illumination variation, the segmentation of apple pixel is difficult. Neural network technology was used to train the algorithm to classify the pixels of images in complex conditions, and hence images with background eliminating could be achieved. Then, for the obtained binary images, the morphological operators were used to optimize the apple edge contour, and the images with smoother apple region could be acquired and each apple edge could be extracted accordingly. Finally, the Circular Hough Transform was used to detect circles from the image and the number of circles was counted as the amount of apples, the centers of the circles were then determined as the center positions of apples in the image.

2 Materials and methods

2.1 Apple tree image acquisition

The experiments were carried out in a commercial apple orchard located in Changping District of Beijing, China (40°14'37.6"N, 116°21'53.2"E). The apple trees in the orchard are in rows, and the apple variety is Red Fuji. The ground view of the orchard is shown in Figure 2, and Figure 3 shows the satellite view of the orchard which was downloaded from Google maps. Analysis of the orchard layout could help to provide a valuable reference for developing orchard yield estimation algorithm. Time of apple tree images acquisition was in mid-October when most apples were ripe. A Cannon 400D camera was used to capture the images in a sunny day and the resolution was 3888×2592.

Four notable features could be discovered from the captured images: (1) the sizes of the apples in an image were varying mainly because of their different distances from camera; (2) the overlaps between apples and the circumstance in which apples were shaded by leaves and branches were ordinary and obvious; (3) illumination was uneven, and thus the shadows greatly affected the color of apples in images; (4) the background of the apples was complicated. The above four characteristics made it more difficult to detect and count apples from apple tree images.

Figure 2 Ground image of the orchard

Figure 3 Satellite image of the orchard

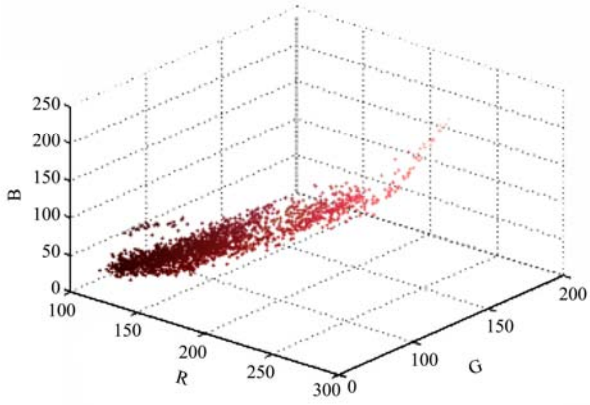
2.2 Apple detecting and counting algorithm

Based on in-depth analysis of the characteristics of apple tree images, this study proposed an algorithm to detect and count apples on the tree images. It consisted of an apple color identifying model to segment the apple pixel region from images and a shape identifying model to detect and count apples.

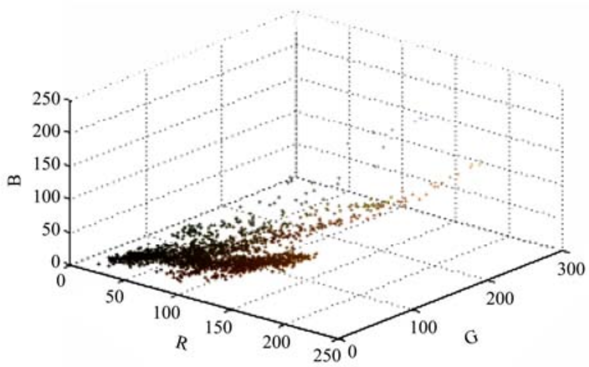
2.2.1 Apple color identifying model

The difference between mature Red Fuji apples and the surroundings in color is significant, thus, RGB color was chosen as the identification feature in apple segmentation. In order to develop the apple segmentation algorithm by using RGB color features, various apple color in different images were sampled and analyzed. Then color distribution maps of apples and background of each image were obtained as shown in Figure 4.

It can be seen in Figure 4, color distribution of apples and background are not completely linear, hence we cannot simply use a threshold to segment the apples from the background like some previous studies[11]. Considering the complexity of color distribution of different targets, NN (Neural Network) modeling was selected to detect apple pixels and eliminate background pixels at the same time. Neural network has been proved to be capable of fitting complex functions[12], a completely trained neural network has a very fast computation speed[13]. Accordingly NN technology was used to establish the targets color classification model.



a. Apple color distribution



b. Background color distribution

Figure 4 Color distribution of targets in an image

A BP neural network of three-layer structure with 6 nodes in hidden layer was built, and Tansig function was used as the transfer function of the hidden layer neuron, a linear transfer function of Purelin was used as the output layer function, and three independent variables of R, G and B were used as the input features for input layer.

The training data sets were apple pixels and non-apple pixels in images obtained from the orchard data acquiring experiments. The apple color identifying NN model was trained using 178 apple images and 39 non-apple images which were intercepted from the experimental images. The targets classification NN model was obtained after training, and it could be used to segment the apple pixels from background with strong robustness and apples in the fruit tree images were identified accordingly. The processing time of this algorithm was less than 1 second per image. One example about the result of the apple segmentation based on apple color identifying model was shown in Figure 6, its original image was Figure 5. From the result it could be concluded that this apple color identifying model could effectively remove the background pixels and segment the apple pixels out.

Figure 5 Image sample of fruit trees

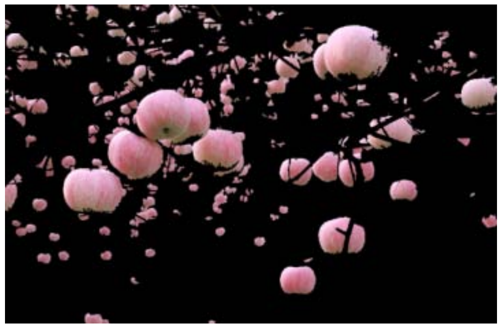


Figure 6 Color segmentation result

2.2.2 Apple shape detecting model

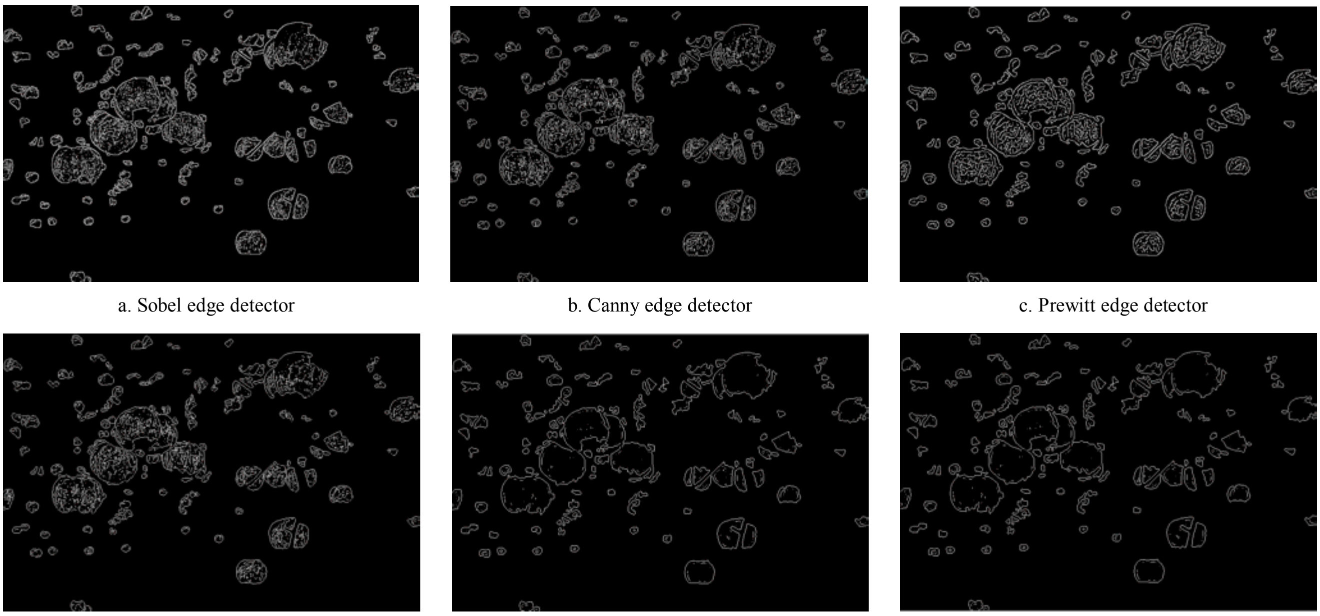
The contour of an ideal apple object can be well described as a circle with the radius within a pre-defined range[14]. Because of individual differences and the impact of the position and angle of the camera shot, apple shapes in images usually present variety. However, in general, the shape of an apple has high similarity with roundness, so that apple partial round contour can be gotten from most of angles. Because of overlapping and shading, the shape of an apple in the image may be shown as an incomplete circle. For example, if the apple is shaded by a tiny leaf, its shape maybe close to a circle; but if the apple is shaded by several long and thick branches, its shape in the image will be divided into several intermittent arc sections. In order to solve the similar detection problems leading to incomplete shape in the image, the circular curve was determined as the standard apple shape, and the Circle Hough Transform was proposed to detect the apples from trees' images.

Hough Transform is a shape positioning technique in image analysis[15]. The purpose of this technique was to find imperfect instances of objects within a certain class of shapes by a voting procedure. This voting procedure was carried out in a parameter space, from this space the object candidates were obtained when the local maxima in this space was found out. With respect to the template matching, fewer computing resources were required by the Hough transform[16]. The parameter space and the voting procedure are defined by Equation (1).

$$\begin{cases} x_0 = x - r\cos(\theta) \\ y_0 = y - r\sin(\theta) \end{cases} \tag{1}$$

In which, the point of (x_0, y_0) represents the center of a circle, and r represents the radius of a circle. For a given range of r, the center of each circle can be detected through Circle Hough Transform algorithm. Accordingly the circle number can be calculated by the accumulation of point of (x_0, y_0).

In order to achieve detecting apples from tree images by using the Circle Hough Transform, edge detection should be executed first in the images without background so that the apple edge images could be obtained. The edge detection has two purposes here, one is to acquire the contours of the apples, and the other is to divide overlap apples into individuals. Considering the textural properties of apples, it is necessary to develop a relatively strong anti-noise edge detection algorithm. This research developed several edge detection algorithms and compared the processing results of these algorithms (Figure 7), and finally the optimal edge detection algorithm was determined.



a. Sobel edge detector b. Canny edge detector c. Prewitt edge detector

d. Roberts edge detector e. Log edge detector f. Zerocross edge detector

Figure 7 Edge detectors

In Hough Transform circle detection algorithm, apple edge pixels were highly concerned, hence the content of noise was adopted for assessing the corresponding edge detection algorithm. After comparing and assessing the detected effects of 6 edge detection operators, it was found that Zerocross detection operator showed the best performance, and accordingly this edge detector was determined as one part of apple shape detecting algorithm. In order to reduce the influence of noise explicitly, the isolated point pixels regions less than 10 pixels were removed, and the obtained final apple shape edge image was shown in Figure 9.

2.2.3 Apple detecting and counting algorithm

The apple detecting and counting algorithm based on apple color identifying model and apple shape detecting model was developed in Matlab2010. The algorithm flowchart is presented as Figure 8, and it consists of the following three major procedures.

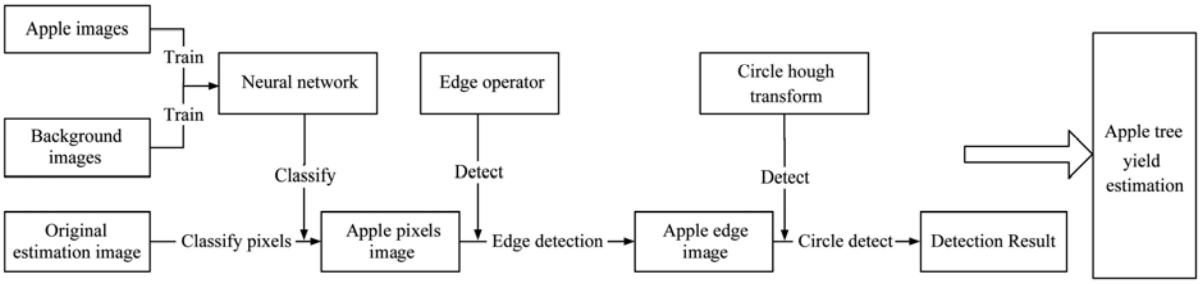


Figure 8 Flowchart of apple detecting and counting algorithm

The first step is to obtain the image which consists of only apple pixels as shown in Figure 7. To achieve this purpose, the background should be eliminated and apple pixels should be retained first. Accordingly the targets classifying NN model was trained by using pixels of both apple color and non-apple color; and then the apple detecting model was obtained and used to classify each image into apple pixels and non-apple pixels; finally the image after classifying pixels was transformed into binary image with only apple pixels left. After that, the hole filling algorithm and morphology open operators were carried out for each binary image, then the obtained image was used to make mask operation with its source image, and finally the apple pixels only contained image with smooth edge profile was obtained for each source image accordingly.

The second step is to obtain the apple edge images as shown in Figure 9, which are the source materials for detecting apples. Since the different apple surface textural properties, the aforementioned edge detecting algorithms left small texture edge points inside the contour of apple, and accordingly those continuous pixel clusters less than 10 pixels in the edge image were removed.

Figure 9 Final apple edge image

The third step is to implement Circle Hough Transform algorithm on each obtained edge image to detect apples as shown in Figure 10. Each circle and its center were detected through Circle Hough Transform algorithm, and the apple amount was then calculated by counting the centers of the apple circles.

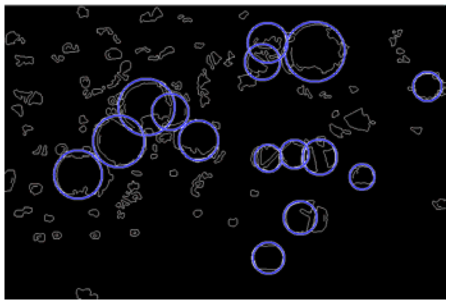


Figure 10 Hough circle detection

3 Results and discussion

3.1 Apple detection

Apple detection result of Figure 5 is shown in Figure 11. It illustrated that the algorithm proposed by this paper had a strong robustness in dealing with the apple recognition problems such as illumination changes, shaded by leaves and branches, and overlaps with other apples. However, apple detecting algorithm would not work effectively if the area of shading or overlapping went too large. In practical use, the parameters of this algorithm can be modified to adapt to specific requirements. For example, the range of radius can be set and changed according to actual target size, the target shape can be modified according to the actual target shape, and the color classification model can be adjusted by training with the specific target color, etc.

Figure 11 Apple detection result

According to the specific application circumstance, the parameters can be adjusted to make the algorithm work effectively and properly. Figure 12 shows the detection results of the algorithm working on other apple tree image samples.

There is little chance for the apple detecting algorithm to generate false detecting results only when it is taking the leaf background as the apple for the reason that the final shape detecting algorithm is carried out based on the apple pixels image. In addition, as there is a range for the parameter of radius, not all circles can be recognized if the apples stayed too far away from the camera and turned to too small in the image. Missing detection also occurs when the occlusion and overlap become too serious. In the actual production, there is no need to detect all apples out especially from far distance. Hence it is enough to detect out the apples in a particular distance range and mark them for a specific operation's need such as picking, counting, etc. The missed apples can be detected in the images acquired after detailed planning the measuring path.

a. Apple detection of sample #1 b. Apple detection of sample #2 c. Apple detection of sample #3

Figure 12 Images of apple detection

3.2 Apple counting validation

In order to verify the robustness of the proposed approach, 15 image samples with different photographic distances and shooting angles were selected to validate the algorithm. The apple detecting and counting algorithm was used to process these images and the results were analyzed. All the big enough apples (r≥2 mm in the images) were counted manually, and then the correlation between the automatic counting results using the algorithm and that of manual work was calculated and the accuracy of the algorithm was obtained. Figure 13 shows the correlation between the results of processing by the algorithm and that of manually counting. Their correlation coefficient of R^2 reached 0.985, and it illustrated that the algorithm proposed in this study had a high accuracy and strong robustness. The result showed that it could be used in orchard apple detecting and counting production and furthermore this algorithm had potential to be used to estimate apple yield.

The proposed algorithm in apple detecting and counting process exhibited a very high accuracy and noise immunity. However, the algorithm cannot completely meet the requirement of the orchard yield estimation independently. A mobile orchard yield estimation system which can avoid repeat counting is still in demand. Orchard automation encompasses the work aimed at increasing farming efficiency and reducing production costs via the deployment of self-guided, low-cost agricultural machines to automate data collection and farm operations[17].

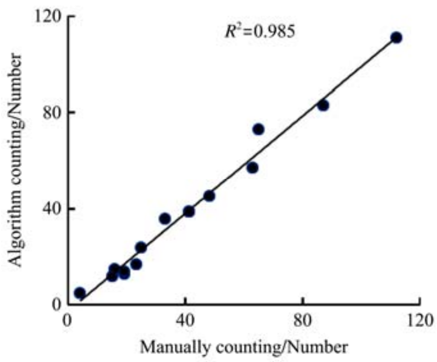


Figure 13 Accuracy of apple detecting and counting algorithm

4 Conclusions

The unavoidable problems were analyzed in detecting and counting apples from apple tree images. An apple detecting and counting algorithm was proposed and the following conclusions were drawn:

1) The algorithm proposed in this study showed a strong robustness in detecting and counting apples from apple tree images since it could deal with the apple recognition problems such as illumination changes, shaded by leaves and branches, overlaps with other

apples, and complex background. The counting results of the algorithm had a high correlation with manually counting and the correlation coefficient of R^2 reached 0.985.

2) The proposed algorithm made full use of the vision features including targets' color and shape to detect and count apples on the tree. The algorithm with strong noise resistance succeeded since the neural network model could fit complex function and Circle Hough Transform provided the incomplete shape detection specialty.

3) The proposed method had strong generalization capability. The algorithm could be extended to the detection of other types of round fruits by re-training the color identifying model of neural network.

4) The proposed approach adapted to the natural conditions and could be used to detect fruits and count their number in tree images, and it could also be used as a core detection algorithm in orchard yield estimation system to provide guidance for the management of the orchard.

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