Kiwifruit recognition at nighttime using artificial lighting based on machine vision

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Abstract: Most researches involved so far in kiwifruit harvesting robot suggest the scenario of harvesting in daytime for taking advantage of sunlight. A robot operating at nighttime can overcome the problem of low work efficiency and would help to minimize fruit damage. In addition, artificial lights can be used to ensure constant illumination instead of the variable natural sunlight for image capturing. This paper aims to study the kiwifruit recognition at nighttime using artificial lighting based on machine vision. Firstly, an RGB camera was placed underneath the canopy so that clusters of kiwifruits could be included in the images. Next, the images were segmented using an R-G color model. Finally, a group of image processing conventional methods, such as Canny operator were applied to detect the fruits. The image processing results showed that this capturing method could reduce the background noise and overcome any target overlapping. The experimental results showed that the optimal artificial lighting ranged approximately between 30−50 lx. The developed algorithm detected 88.3% of the fruits successfully.

Keywords: Elliptic Hough transform, image capturing method, Kiwifruit, minimal bounding rectangle, optimal illumination intensity
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1 Introduction

China is the largest country for cultivating kiwifruits, where the province of Shaanxi provides the largest production which accounts for approximately 70% of the local production, and 33% of the global[1]. In 2011, the cultivation area of kiwifruits in Shaanxi was around 4.72×10^4 hm^2, while the production reached 7.36×10^5 t, which made Shaanxi the largest plantation area in the world[2,3]. Harvesting kiwifruits in this area relies mainly on manual picking which is labor-intensive. Therefore, there is a strong desire to introduce mechanical harvesting.

Kiwifruits are commercially grown on sturdy support structures, such as T-bar and pergola[4]. The T-bar trellis is common in China because of its low cost. It consists of a 1.7 m high post and an approximately 1.7 m wide cross arm which may vary slightly in width according to the geometry of the orchard. Wires run on

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the top of the cross arms connecting them to each other at the middle and at both sides of the cross arms. The upper stems of the kiwifruit are tied to the top wires so that the egg-sized kiwifruits would be hanging downward which makes them easy for picking in the harvesting season[5,6].

Similar to other orchard fruits, such as apples and oranges, it is necessary to design an intelligent robotic machine with human-like perceptive capabilities, such as the ability to visualize the fruit and calculate its position, so as to mechanize the harvesting task. Machine vision has been the method widely used in robotic harvesting. Its applications have been studied on apples[7,8], oranges[9-12], and tomato[13]. A color CCD camera was used to capture original apple images as well as an industrial computer for processing images to recognize and locate the fruit in a harvesting robot[7,8]. Hannan et al.[11] applied machine vision to recognize oranges by detecting fruit color and shape with developed image processing algorithm. Muscato et al.[12] developed a vision-based citrus harvesting robot prototype called CRAM, where a differential image size of the fruit was used to identify the distance, thus, avoiding additional range measurement sensors. Mehta and Burks[10] used a combined vision system in their robotic manipulator which consisted of a fixed camera for providing a global view of the tree canopy and a camera-in-hand for supplying high resolution fruit images.

For kiwifruits, Ding et al.[14] used R-B color parameters for fruit segmentation on natural backgrounds, but they did not identify each single fruit. Scarfe et al.[15] employed an intelligent computer vision system in their autonomous kiwifruit picker to identify fruits hanging from the canopy, and to discriminate them according to sizes and gross defects. Wu et al.[16] applied Haar training to identify fruits and the watershed algorithm to separate adjacent fruit objects. Cui et al.[17] studied the method of fruit recognition and feature extraction based on color and shape features of kiwifruits outdoor at daytime. Zhan et al.[18] developed an image processing technique based on an Adaboost algorithm to segment kiwifruits from the background. Mu et al.[19] employed Lab color space to extract characteristic parameters of kiwifruits by using Canny operator for edge detection and ellipse Hough transformation for fruit recognition. All researches involved so far in kiwifruit harvesting suggest the scenario of harvesting in daytime taking advantage of the sunlight. However, for a massive production such as the one takes place in Shaanxi, it is desirable to develop a harvesting robot which can work all day round during the busy season. This can be a similar approach to the strawberry robotic harvesting machine which harvests strawberries grown inside greenhouses[20]. This machine is provided with a machine vision system of artificial lighting and background to enable harvesting at any time during the day and night.

A robot operating at night can overcome the problem of low work efficiency and would help to minimize fruit damage, as the fruit temperature is lower than that during the daytime. In addition, artificial lights can be used to ensure constant illumination instead of the variable natural sunlight for image capturing. Scarfe et al.[15] also utilized artificial lights to improve their automated kiwifruit picker by employing floodlights if the light level is not enough for the vision system. However, detailed information of the lighting and the optimal artificial illumination were not reported and discussed.

In previous studies[16-19,21], kiwifruit images were captured by locating the cameras near the underside of the canopy and its central axis approximately parallel to the canopy. This caused the background of the images to contain pendulous foliage or remote non-target fruits, which would add excessive noise in image segmentation, and thus influence accuracy. Moreover, target fruits in the images might overlap since kiwifruit grows in clusters. This also caused difficulties to identify each target fruit and decreased recognition accuracy.

Therefore, in this paper, a night machine vision system for kiwifruit was designed and tested. The system included an image capturing method, optimal artificial illumination investigation, and an image processing algorithm. First, the fruit images under different illuminations were captured for analyzing. Next, different images under the suggested conditions were acquired. Finally, an image processing algorithm was developed to recognize the fruits.

2 Materials and methods

2.1 Image capturing

The common kiwifruit image capturing method used in other studies was a camera located beneath the canopy with its central axis is approximately parallel. However, image captured by this method includes quite non-target fruit objects. Besides, the target fruit are overlapping each other. It would cause difficulties to identify each target fruit and would decrease the recognition accuracy. The night kiwifruit image capturing method was thus proposed according to the growth characteristics of kiwifruits. Since kiwifruits are commercially grown on sturdy support structures, the image capturing method used in this study was based on placing the capturing camera underneath the fruits, so that its central axis would be perpendicular to the canopy. In this condition, only the target fruits could be included in the camera field of view, and the fruits would be adjacent to each other instead of overlapping.

Images of the fruits were taken in late October during the harvesting season on the most common cultivar 'Hayward' at the Meixian Kiwifruit Experimental Station (34°07'39"N, 107°59'50"E, and 648 m in altitude) at the Northwest A&F University. A very common CMOS camera (Microsoft, LifeCam studio) with a resolution of 640×360 was placed at 20 cm underneath the fruits plane so that a cluster of kiwifruits could be included in the field of view (36 cm × 20 cm in actual size approximately) of the camera. The camera, in turn, was connected to a computer (ThinkPad T400, 2.53 GHz) for saving the fruit images. Figure 1 shows an example of the experiment set up, while Figure 2a shows an example of how the objects appear in the images. In a total of 25 clusters with 95 fruits (5 clusters with 20 fruits at October 26, 2013, 10 clusters with 40 fruits at October 23, 2014, and 10 cluster with 35 fruits at October 27, 2014) were captured to develop the machine vision system, while 103 images (36 images at October 26, 2013, 33 images at October 23, 2014, and 34 images at October 27, 2014) containing clusters which varied between 2 and 5 fruits were captured to test the system.

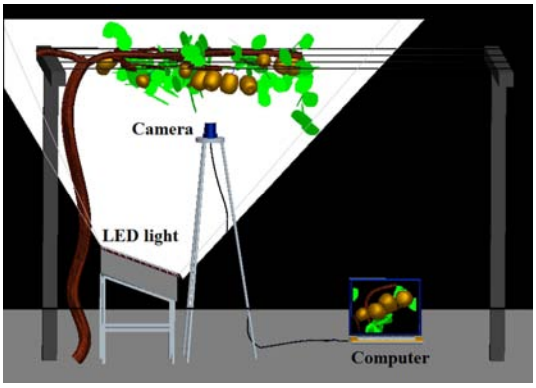
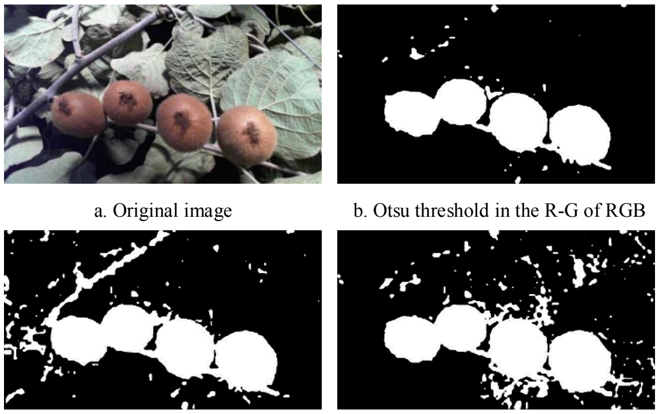


Figure 1 Schematic diagram and picture of the image capturing system



a. Original image
b. Otsu threshold in the R-G of RGB
c. Otsu threshold in the V of YUV
d. Otsu threshold in the I of YIQ

Figure 2 Original image and segmentation with different method

2.2 Illumination

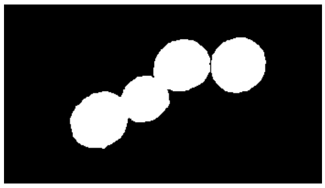
The illumination at night outdoor under bright moon was near to 0.1 lux, while that around the kiwifruits under leaves was found to be less than 0.1 lux as measured by a light meter (TES-1332A Light Meter, TES Co., Taiwan). This is considered to be too low to distinguish a fruit from a background. Besides, the nights of bright moon are very limited to the few nights of full moon, provided that these nights are not cloudy. Also, the illumination under bright moon does not exceed few lux in the canopy while the lighting system has much higher illumination value so in total the moon light does not affect an artificial lighting system. Therefore, an adjustable panel light source (CM-LED 1200HS, KEMA Co., Wuhan, China) with 1 200 light-emitting diode (LED) chips was applied. In order to provide homogeneous illumination around the target fruits, the LED light was set on a 30 cm height stand at approximately 1 m away from the target fruit in average.

An appropriate light intensity is necessary for image segmentation and fruit recognition. If the intensity is too low, the fruits may have jagged edges when segmented. On the contrary, too high light intensity would cause some parts of the fruit to over reflect forming large holes in the image segmentation. Therefore, 12 light levels (10, 30, 50, 80, 110, 150, 200, 300, 400, 500, 800 and 1 200 lux) were experimented to study the optimal illumination. The fruits illumination was estimated by averaging the illumination values measured three times at three different locations around the target fruit cluster.

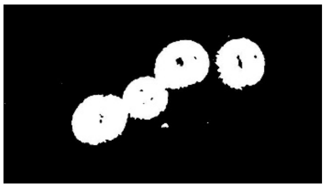
The optimal illumination was determined by analyzing the kiwifruit color characteristics. It was necessary to find an adequate color space for color image segmentation. Therefore, six common color spaces RGB, L*a*b*, HSI, Ohta, YIQ and YUV, were compared. The histogram of kiwifruit images was distinctively bimodal in the R-G of RGB, V of YUV, and I of YIQ. The threshold which separates the pixels in the intensity histograms into two classes was found using the Otsu method[22]. This method was applied on the R-G, V and I images as shown in Figure 2 which shows that most of the leaves could be eliminated in the R-G images. Since better segmentation results were expected by adding a coefficient as nR-G[17], the R-G model was selected for image segmentation. In order to find the optimum coefficient n, seven levels, from 0.8 to 1.4 with 0.1 increments, were arbitrarily tested.

The optimal illumination and the optimal coefficient were assessed based on comparing the number of pixels segmented in images of 25 clusters, which contain in total 95 kiwifruits. Since 12 light illumination levels and 7 increments of the n coefficients were tested, 84 images of each cluster were generated to find the optimal combination of these two factors. These images were compared by applying the Otsu method in each image and counting the number of misclassified pixels. These pixels could be determined by comparing each image with a standard image segmented manually using the magnetic lasso tool in the Adobe Photoshop CS5. Figure 3 shows an example of an image of fruit cluster segmented manually using the magnetic lasso tool (Figure 3b), while Figure 3c is the image segmented using the Otsu method when the illumination was 50 lux and the coefficient n was 1.0.

a. Original cluster



b. Cluster segmented manually



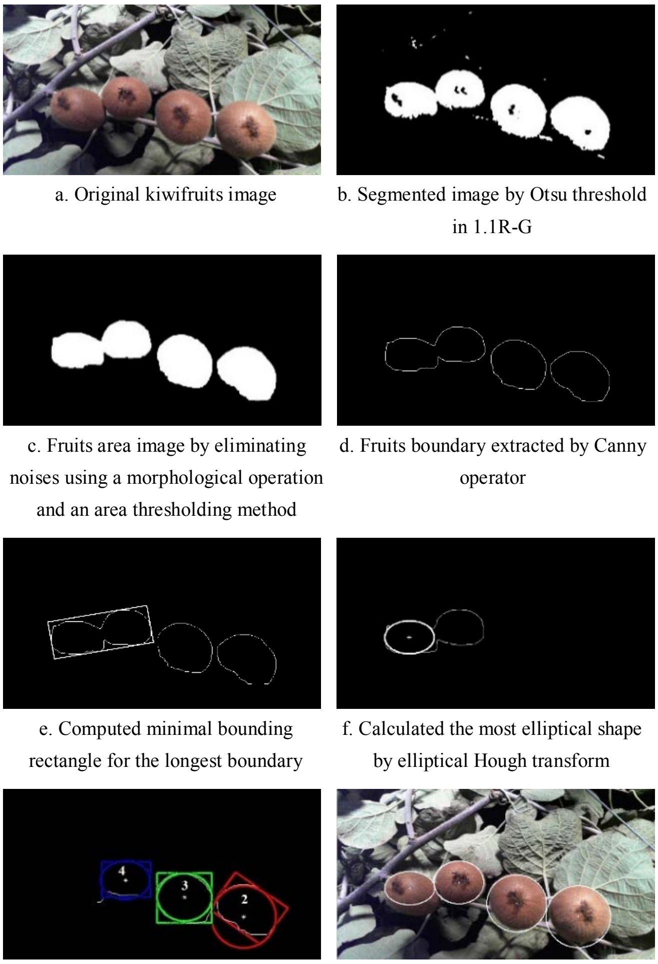
c. Cluster segmented at illumination 50 lx and n is 1.0

Figure 3 Original cluster image and segmented images

2.3 Fruits recognition

After isolating each cluster of the kiwifruits under the optimal lighting conditions and using the optimum n coefficient, the next method was to detect the fruits within the cluster. Figure 4 shows an example of detecting the individual fruits while Figure 5 is the flowchart of the algorithm developed for the kiwifruits detection. Firstly, a morphological operation was applied to remove noise that adheres to the target fruits, such as branches, so that Figure 4b could be obtained. Next, an area thresholding method was employed to eliminate the small area noises remaining in Figure 4b. This method is based on finding the biggest area of neighboring white pixels in the image and eliminating all areas which are smaller than 1/5 of the biggest area. Figure 4c shows the noise-free fruit image, whose boundaries were extracted by the Canny operator[23], as shown in Figure 4d.

By now, there are a number of methods for detection of clustered objects. For detecting in-line potato tubers without singulation, Al-Mallahi et al.[24] developed an algorithm based on the principle of scanning images from left to right until encountering a cluster, around which a periphery scanning starts until a sudden shrinkage in its width occurs, indicating the existence of a contact point. However, it is optimal for the line-arranged objects. A more often used approach is to detect ellipses which are powerful shapes can cover nearly almost every part of a plant. From round fruits, complex leaves to long small objects (lines) like stems. Pastrana and Rath[25] simplified the complexity of leaf shapes by using ellipse



a. Original kiwifruits image

b. Segmented image by Otsu threshold in 1.1R-G

c. Fruits area image by eliminating noises using a morphological operation and an area thresholding method

d. Fruits boundary extracted by Canny operator

e. Computed minimal bounding rectangle for the longest boundary

f. Calculated the most elliptical shape by elliptical Hough transform

g. Repeat (e) to (f) on the left fruit boundary after removing the determined fruit object boundary until all the fruit objects were recognized

h. All the determined fruit objects and their central positions

Figure 4 The process of recognize fruit objects

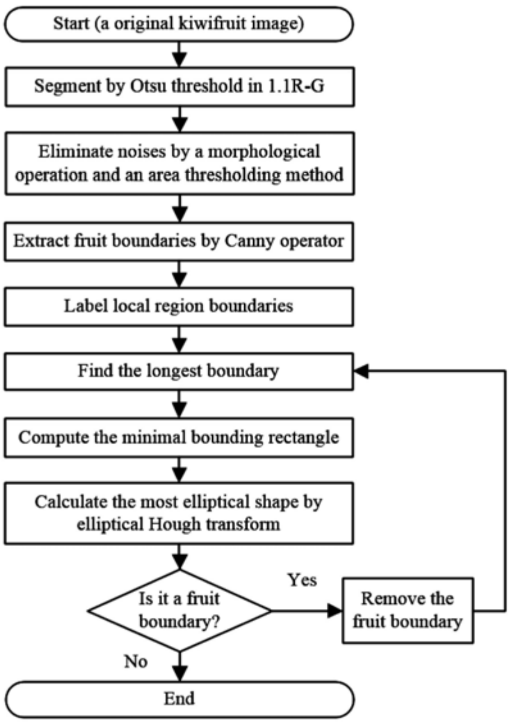


Figure 5 Flowchart of the process to recognize fruit objects

approximation to overcome the overlapping problem which also showed good results on cucumber, tomato, and serrano pepper. Since kiwifruits are elliptical shapes in a 2D image, elliptical Hough Transform was applied to locate the fruit objects on the images which being captured by the common method. When being observed from the fruit bottom, kiwifruits are also in ellipses with an eccentricity of 0.39 in average. Therefore, kiwifruits were recognized by detecting ellipses using the Hough Transform (HT) in this study.

A minimal bounding rectangle[26] and an elliptical Hough transform[27] were applied to recognize each target fruit area. First, the local region boundaries were labeled in the fruit boundaries image. Then, the longest boundary was extracted and its minimal bounding rectangle was computed by finding the minimum and maximum values in the horizontal and vertical axes, as shown in Figure 4e. The elliptical Hough transform, which is a method to detect ellipses using the Hough transform, was next employed to calculate the most elliptical shape (Figure 4f) within the rectangle and judge it is a fruit boundary or not by comparing it to the nearest boundary pixels. If the number of boundary pixels that near to the calculated ellipse are more than 50% of the calculated ellipse, it will be specified as a fruit boundary and a search for a new fruit will start. The process iterates until all boundaries in all clusters are detected, as shown in Figure 4g.

3 Results and discussion

3.1 Optimal illumination and optimal coefficient of *n*R-G

Figure 6 shows the misclassified pixels of the kiwifruit images of 7 different coefficients n of the nR-G model at 12 different illumination levels. At all levels, the least number of misclassified pixels was obtained when n was equal to 1.1, which was selected to be the optimal coefficient used in image segmentation.

For different clusters, the misclassified pixels varied greatly among the 5 clusters. In order to eliminate the effect of variation due to changes in the testing images, a normalization technique was employed to minimize this effect. For each image of one cluster, Equation (1) was applied to find the ratio of misclassified pixels in comparison with the image of the least number of misclassified pixels at each cluster

$$a_{ij} = A_{ij} / \min(A_i) \qquad (1)$$

where, A_{ij} is the number of misclassified pixels of jth image in the ith cluster; $\min(A_i)$ is the least number of misclassified pixels of an image in the ith cluster; a_{ij} is the normalized value (ratio); i is from 1 to 5 with 1 increment, and j is from 1 to 12 with 1 increment.

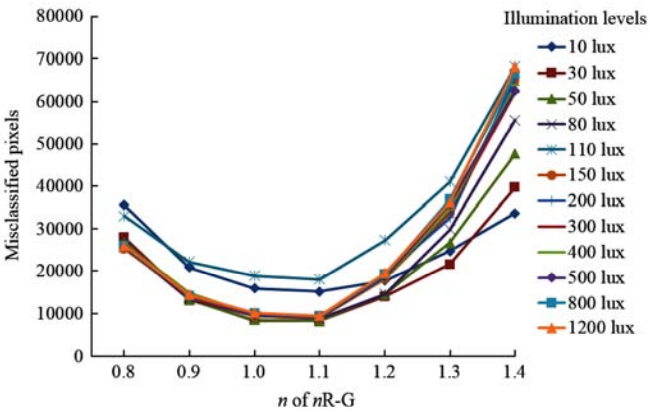


Figure 6 Error segmented pixels of kiwifruit images of 7 different coefficients n of nR-G at 12 different illumination levels

Figure 7 displays a boxplot of the normalized misclassified pixels of the five clusters at the 12 different illumination levels. The boxplot shows that the misclassified pixels increase with illumination level as well as the interquartile rages and whiskers. The illumination level at 30 lux was found as an optimal choice with a normalized misclassified pixel ratio of 1.09±0.05 as it has the smallest deviation and average, whereas the distribution spans ranged from 1.02 to 1.15. Similarly, the illumination level at 50 lux also has the smallest average of 1.09 and shows the highest sig. (two-tailed) of 0.983 of the paired samples t-test to the illumination level of 30 lux (PASW Statistics 18, SPSS Inc., an IBM Company, Chicago, Illinois, USA). Furthermore, high illumination levels needs high power and thus consume more energy. Considering the difficulty in fixing the illumination on a one single value, the illumination levels from 30-50 lux were selected as the optimal lighting range for the vision system.

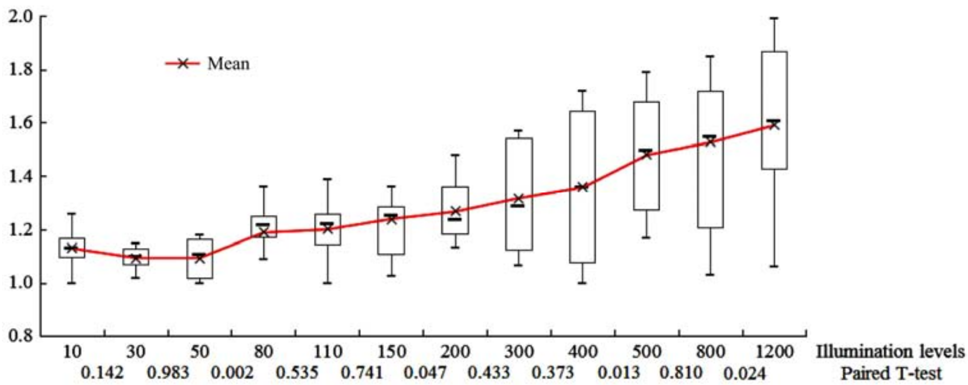


Figure 7 Boxplot of the normalized error segmented pixels of the five clusters at the 12 different illumination levels and the paired samples t-test results

3.2 Fruits recognition

Table 1 shows the number of fruits detected according to the number of objects in one cluster. The number in the brackets shows the percentage of the undetected, missing and successfully detected fruits in each category and in total. The undetected fruits are the ones within the field of view of the camera but not detected by the algorithm during the image processing. On the other hand, the missing fruits are the ones detected during the image processing but their locations were not determined correctly by the algorithm.

Most of the examined clusters consisted of 3 to 5 fruits (95.1% of the total number of clusters). Only five clusters consisted of 2 fruits in the randomly selected clusters. This is in accordance with a field survey which showed that most of the kiwifruit clusters include 3 to 5 fruits.

Table 1 Number of fruits being recognized at the different numbers of fruit objects in the cluster

	5-Fruit cluster	4- Fruit cluster	3- Fruit cluster	2- Fruit cluster	Total
Fruits number	150	144	96	10	400
Undetected fruits	22 (14.7%)	16 (11.1%)	9 (9.4%)	0 (0.0%)	47 (11.8%)
Missing fruits	16 (10.7%)	13 (9.0%)	6 (6.3%)	0 (0.0%)	35 (8.8%)
Correctly recognized fruits	128 (85.3%)	128 (88.9%)	87 (91.6%)	10 (100%)	353 (88.3%)

The success rate was decreasing as the number of fruits increased in a cluster. In a cluster of 2 fruits, the success rate was 100%. On the other hand, the success rate was 91.6%, 88.9% and 85.3% for cluster of three, four, and five fruits respectively.

Moreover, the number of missing fruits also increased as more fruits included in a cluster. For all the images, the missing rate increased from 6.3% of 3-Fruit cluster to 9.0% of 4-Fruit cluster, and to 10.7% of 5-Fruit cluster, respectively.

It was found that undetected and missing fruits appeared mostly at the same cluster where a fruit was adjacent to three or more fruits (as shown in Figure 8a) in contrast to being adjacent to less than three fruits (as shown in Figure 4a). In this condition, the outmost and less adjacent fruits were correctly recognized firstly since they had longer boundaries, while the inner and more adjacent fruits were undetected or missing as the left boundary was not enough to form a fruit object, as shown in the Figure 8d. A possible solution could be to exploit the angle where a fruit boundary turns toward another fruit. On the other hand, most clusters (87.3% of the examined clusters) are linearly arranged on the branches which are suitable for the proposed algorithm, only 6.1% of the examined fruits are adjacent to more than 2 other fruits.

a. Recognized objects on original image

b. Segmented object image

c. Extracted fruits boundary by Canny operator

d. Left fruits boundary after removing the boundary of correctly recognized fruits (the outmost and less adjacent fruits)

Figure 8 Example of un-detected and missing fruit objects

In total, 353 fruits (88.3%) were correctly recognized with 47 fruits (11.8%) were undetected, and 35 fruits (8.8%) were missing. It takes 0.83 s on average to segment an image, and 1.51 s to recognize each fruit on average (ThinkPad T400, 2.53 GHz).

4 Conclusions

In order to develop a robot to harvest kiwifruits at night and overcome the problems of the complex background and fruit overlapping by the conventional fruit image capturing method at daytime, a machine vision system was proposed in this study. It included an image capturing methodology in which a camera was placed underneath the fruit canopy to obtain fruit images, and an employment of artificial lighting to ensure constant illumination, as well as the development of an image processing algorithm to detect the fruits.

The results showed that the optimal illumination level was at the range of 30-50 lux. The successful recognition rate of 88.3% was obtained with the developed algorithm. It was found that the successful rate was decreasing as more fruits were included in a cluster while the missing fruits were increased. Besides, the undetected fruits and missing fruits mostly appeared at the same cluster where one fruit was adjacent to three or more fruits. An improved algorithm is thus necessary to be studied by utilizing the angle, at where a fruit boundary turns toward another fruit.

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