Accurate and rapid image segmentation method for bayberry automatic picking via machine learning

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Abstract: Due to the short ripening period and complex picking environment, bayberry generally relies on mechanical equipment for picking, especially the automatic picking system guided by vision. Thus, it is crucial to locate the bayberry in the view accurately and rapidly. Although efforts have been made, the existing methods are difficult to implement due to the limited amount of data and the processing speed. In this study, an accurate and rapid segmentation method based on machine learning was proposed to address this problem. First, the images collected by the visual guidance system were pre-processed by contrast-limited adaptive histogram equalization (CLAHE) based on the Y component of the YUV color space. Taking advantage of the color difference map of RB and RG for the segmentation of different colors, an adaptive color difference map foreground segmentation method was then adopted for bayberry region foreground segmentation. Finally, distance transforms and marking control watershed methods were exploited to achieve single bayberry fruit segmentation. Furthermore, with the help of the convex hull theory and fruit shape characteristics, the irregular background interference areas were filtered out, which improved the accuracy of bayberry segmentation performance. The experimental results show that this method can achieve better segmentation of bayberry in complex orchard environment with an accuracy of 97.4% and only takes 0.136 s to calculate once.

Keywords: bayberry, image segmentation, machine learning, automatic picking, computer vision
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1 Introduction

Bayberry is a characteristic fruit in southern mountainous areas in China such as Guangdong and Hunan. It has high nutritional and economic value[1,2]. Bayberry has a short maturity period, and the fruit quickly rots and drops after maturity. Therefore, timely harvesting of the fruit is a necessary measure to reduce losses and improve fruit quality. The use of artificial intelligence and automation technology through automatic mechanical harvesting methods can effectively save picking costs, improve picking efficiency, and reduce fruit damage. Therefore, to improve the validation results of the picking manipulator and realize the automatic bayberry picking function, research on the accurate detection and automatic location of bayberry fruit is of great significance.

At present, automatic fruit-picking machines based on machine vision have been gradually applied to agricultural production[3]. However, due to the influence of light intensity changes in the natural environment of the orchard, complex backgrounds, and occlusion of branches and leaves, there is still inaccurate fruit segmentation and detection, which restricts the practical application of automatic fruit picking machines in bayberry orchard environments. At present, many scholars have performed numerous studies on the combination of single or multiple biological characteristics, such as the color, shape, and texture of the fruit[4-7]. Wang et al.[5] proposed an improved wavelet transform and Retinex-based image enhancement algorithm to highlight images under various lighting conditions and used *K*-means clustering to segment fruit regions. Lu et al.[8] proposed a local binary mode texture feature and Hough circle transformation method, which utilized the light intensity distribution of fruit surface to analyze the hierarchical contour of fruit region with an accuracy of 82.3%. Si et al.[9] used the color difference ratio method to identify the apple target and then used the random circle method and matching algorithm to locate the apple. Xu et al.[10] proposed a bayberry image segmentation algorithm based on the salient target detection method of manifold sorting to achieve accurate segmentation of red bayberry. He et al.[11] carried out a multiscale description of citrus from the three aspects of shape, texture, and color and proposed a green citrus detection method based on a deep bounding box regression forest (DBBRF), which realized the detection of green citrus in a natural environment. However, from the perspective of image processing, the biological characteristics of these fruits cause light spots and shadows due to changes in natural light and lead to changes in fruits, leaves, and background colors, thereby increasing the error rate of fruit detection, usually due to the orchard environment. There are many problems, such as fruit overlap, occlusion, and background interference, and it is still difficult to

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achieve accurate locating of different colors of bayberry.

In recent years, detection methods based on deep learning have become increasingly popular. Bargoti et al.[12] used the multiscale and multilayer perceptron neural network convolution capturing context information of image data to achieve simple segmentation of fruit. Using watershed segmentation and the cyclic Hough transform algorithm, the author segmented the fruits at the pixel level. This method realizes the detection and counting of apples in orchards. Li et al.[13] proposed an integrated U-Net segmentation model combining residual blocks and gated convolution. More multiscale context information and edge features are retained through the ATROS convolution and ATRUS spatial pyramid pool structure. This improves the accuracy of fruit segmentation and the generalization ability of the model. Yu et al.[14] proposed a strawberry fruit segmentation and picking point location method based on Mask-RCNN to improve machine vision performance in strawberry harvesting robot fruit detection. Although this method based on deep learning has achieved good performance, the number of samples required for training is extremely large under various conditions, and it is difficult to collect many samples in practical applications. At the same time, the training and reasoning of the algorithm largely depend on high-configuration hardware equipment, complex reasoning models, and poor real-time algorithms, which are difficult to apply to agricultural machinery equipment, especially in picking manipulators operating in hilly and mountainous field environments.

In the past 10 years, there have been many studies[12-14] on how to accurately identify fruits. Some scholars[15] have also focused on using color RGB images and deep learning to realize real-time crop differentiation. However, there are still few works on the location and segmentation of bayberry fruits in the complex environment of orchards under natural light conditions. To handle this, in this manuscript, based on machine vision, a new method for bayberry automatic locating and segmentation in an orchard environment is proposed. The main contributions are as follows:

1) Based on local adaptive image enhancement technology, a new framework was proposed for bayberry automatic locating and segmentation under natural lighting conditions;

2) An improved adaptive color difference segmentation method was proposed. By combining this method with the flood-filling algorithm, the accurate locating of bayberry fruits in potential foreground regions is realized;

3) A single fruit region location and shape estimation method based on the marking control watershed and convex hull theory was designed. According to the fruit area shape feature filtered interference area, the segmentation accuracy of bayberry under the orchard environment was improved.

2 Materials and methods

2.1 Experimental image acquisition

The experimental images were collected from the natural bayberry orchard of Guangzhou Conghua Fruit and Vegetable Fresh Co., Ltd., China, and were taken by CMOS sensor equipment deployed on mobile devices (iPhone 5S) during the bayberry ripening period in May 2018. All images were collected 20-80 cm away from bayberry fruit in different weather conditions, and the image resolution was unified at 640×480 pixels. The figures include immature and mature bayberry images under different illumination conditions. The total amount of collected images is 105, all of which were used as experimental test data. The images shown in Figure 1 illustrate several examples.

a. Mixing of fruits at different stages b. Occlusion for complex scenes

c. Low illumination d. High illumination

Figure 1 Bayberry images collected in the natural environment of the orchard

All experiments were performed in the Visual Studio Code environment of the Windows 10 operating system, based on the Python-OpenCV library, using Python language programming. The main hardware configuration of the experimental environment is an Intel Core i7-9750H CPU; memory: 16 GB DDR4; GPU: NVIDIA Geforce GTX 1660 Ti GPU.

2.2 Bayberry fruit segmentation method

Figure 2 shows the bayberry fruit segmentation process, which mainly includes three parts: 1) Local adaptive image enhancement; 2) bayberry fruit region foreground segmentation; 3) background interference region filtering.

2.3 Local adaptive image enhancement

When collecting data, the bayberry surface was affected by uneven illumination and shooting angles. When the illumination distribution is relatively uniform, traditional histogram equalization may make some image areas become “overexposed”. Therefore, to improve the image brightness without changing the color information of the red bayberry fruit, a local adaptive image enhancement method (named LAIE) based on the YUV color space and CLAHE[16] was designed. It consists of extracting the Y component representing the brightness of the image in the YUV color space. The Y component image was divided into multiple subblocks of the same size to perform local histogram equalization, thereby improving the uneven distribution of image gray values and image clarity.

The specific algorithm process is as follows:

Step 1: Extract the Y component channel in YUV and divide the channel image into several subblocks of the same size;

Step 2: Apply histogram cropping on each divided subblock and calculate the average value of the subblock pixels, as shown in Equation (1).

$$N_{\mathrm{ave}} = \frac{N_x \cdot N_y}{N_{xy}} \tag{1}$$

where, N_{ave} represents the average value of the pixel; N_x represents x number of pixels in the direction; N_y represents y number of pixels in the direction; N_{xy} represents the number of grayscales of the subblock region.

Step 3: Calculate the limited contrast value,

$$C = N_c N_{\mathrm{ave}} \tag{2}$$

where, N_c is the pixel cropping coefficient.

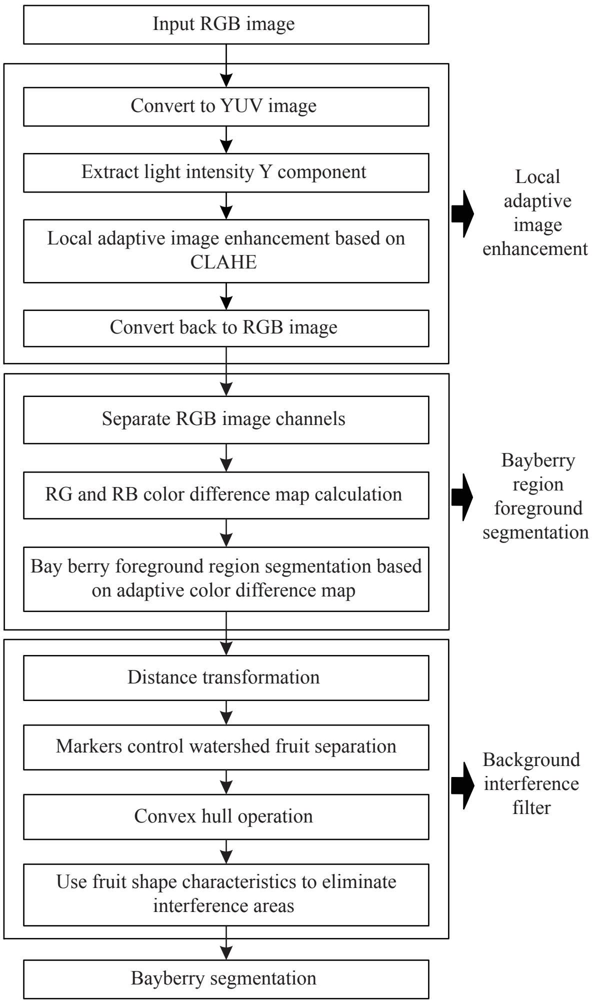


Figure 2 Flow chart of the bayberry segmentation method

Step 4: The subblock area is processed based on the cropping coefficient N_c, and the number of pixels S after the processing is calculated. The pixels are equally distributed; that is, the pixels N_v after the even distribution is shown in Equation (3).

$$N_v = \frac{S}{N_{xy}} \tag{3}$$

Step 5: For the pixel values beyond the set pixel range after cropping, Equation (4) was used to find them and redistribute them (as shown in Figure 3).

$$L = \frac{L_G}{S} \tag{4}$$

Step 6: Apply histogram equalization on the subblocks of the above steps.

Step 7: Use the linear difference algorithm to solve the effect between subblocks.

Obtain the corrected intensity Y ′, keep the U and V components of the YUV color space unchanged, replace the original intensity component Y with Y′, and transform the YUV color space back to the RGB color space to generate an enhanced color image.

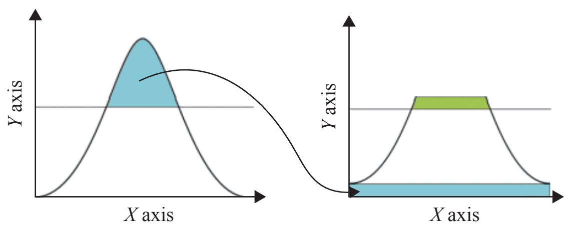


Figure 3 Schematic diagram of CLAHE processing

2.3.1 Bayberry segmentation in the natural environment

In the wild environment, the images collected from the orchard all contained complex natural scenes with several types of occlusion, such as bayberry, leaves, branches, tree trunks, grass, and sky. Although it is possible to use a single-color component or the characteristic relationship of each color component to perform image segmentation to obtain different targets, the area of bayberry fruits is small, and there are many growing positions. As a result, bayberries of different shapes also exist in the background of the captured image. Simple use of color segmentation cannot remove the “bayberry noise” of the background without changing the bayberry’s shape in the foreground area.

To effectively segment the bayberry area and filter out background interference, the red bayberry fruit area containing different maturity levels and the background area containing different objects were extracted from the data set (the composed image is shown in Figure 4a). In Figure 4a, the red horizontal line passes through the bayberry and calculates the difference between the R component and G component, and the R component and B component in the RGB color space of the pixel (as shown in Figure 4b). In Figure 4b, the area where the pixel positions of the x-axis are between 0 and 600 is the bayberry fruit area, and the area where the pixel position of the axis is between 600 and 1200 is the background area. It is easy to see that the RG and RB color difference values of the bayberry fruit area are significantly higher than the background area, the RB color difference value shows a small fluctuation in the background area, and the RB color difference value in the immature bayberry area is significantly higher than the RG color difference value. The color difference maps of RB and RG in the immature bayberry region, mature bayberry region, and background region are shown in Figures 4c, 4d and 4e, respectively. For the mature bayberry region, RG color difference value is higher than the RB color difference value (Figures 4b and 4d). Therefore, to combine the advantages of the color difference map of RB and RG and reduce the background noise interference introduced by the RB color difference map, segmentation based on adaptive chromatic mapping (ACMS) was proposed to achieve different maturity segmentation accuracies of bayberry fruits.

Assuming that I_{RG} and I_{RB} are the R-G color difference map and R-B color difference map respectively, the calculation equations are as follows:

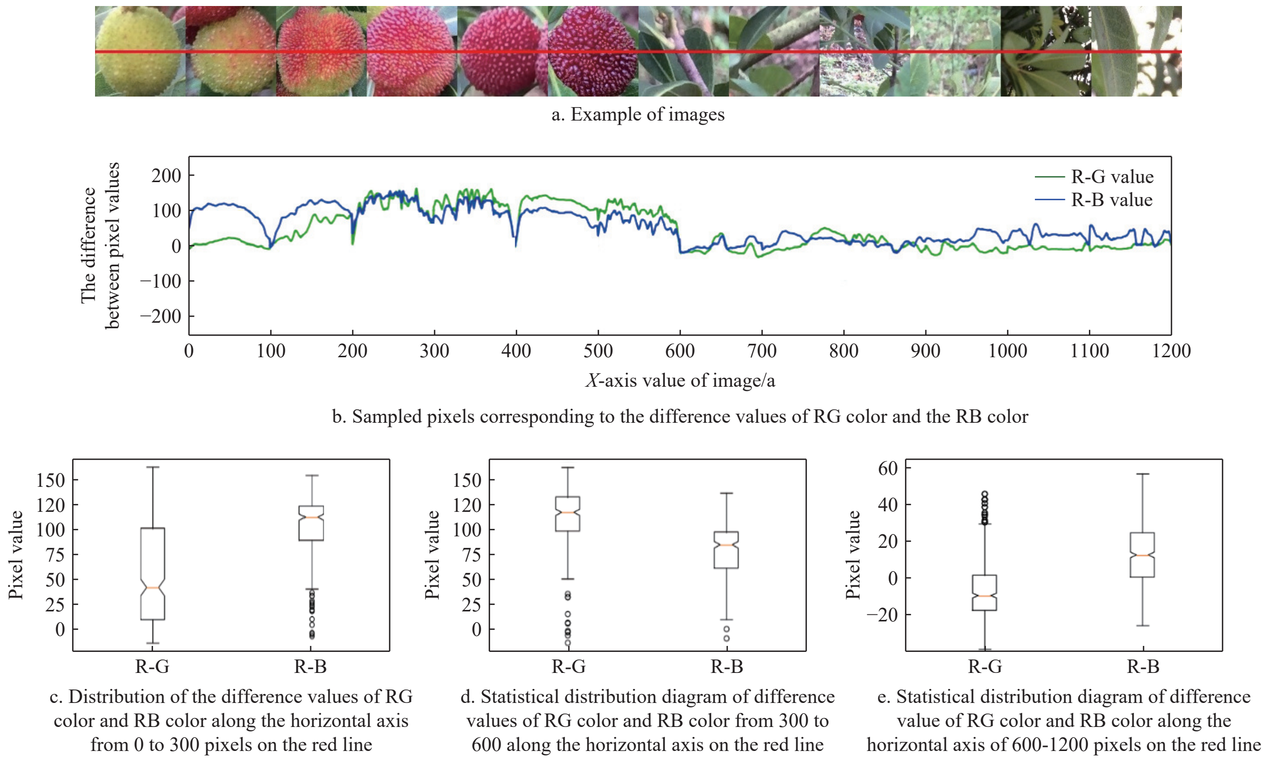
$$I_{\mathrm{RG}} = \begin{cases} I_R - I_G, & I_R \geq I_G \\ 0, & I_R < I_G \end{cases} \qquad I_{\mathrm{RB}} = \begin{cases} I_R - I_B, & I_R \geq I_B \\ 0, & I_R < I_B \end{cases} \tag{5}$$

where, I_B is the B component in the image RGB color space; I_G is the G component in the image RGB color space; I_R is the R component in the image RGB color space.

To realize the fusion of the RG color difference map and the RB color difference map I_{RG}, the Otsu algorithm[17] was combined, and the calculation formula of the binary map of the fruit potential region ($I_{f\mathrm{cmt}}$) can be obtained as follows:

$$I_{f\mathrm{cmt}} = f_{\mathrm{Threshold}}(I_{\mathrm{RB}}) \cup f_{\mathrm{Otsu}}(I_{\mathrm{RG}}) \tag{6}$$

where, $f_{\mathrm{Otsu}}(\cdot)$ is the Otsu function; $f_{\mathrm{Threshold}}(\cdot)$ is the image thresholding function. By customizing the threshold T, the noise effect introduced by the RB color difference map can be significantly reduced. The threshold T is calculated as follows:



a. Example of images

b. Sampled pixels corresponding to the difference values of RG color and the RB color

c. Distribution of the difference values of RG color and RB color along the horizontal axis from 0 to 300 pixels on the red line

d. Statistical distribution diagram of difference values of RG color and RB color from 300 to 600 along the horizontal axis on the red line

e. Statistical distribution diagram of difference value of RG color and RB color along the horizontal axis of 600-1200 pixels on the red line

Note: Red line in Figure 4a is the pixel count.

Figure 4 Statistical results of the difference in the color component of bayberry and background area

$$T = \frac{\text{mean}(V_f) + \text{mean}(V_b)}{2} \tag{7}$$

where, mean(·) is the mean value-solving function; V_f is the R-B pixel value of the fruit region in the image; V_b is the R-B pixel value of the background region, as shown by the blue line in Figure 4b.

It should be noted that there is a significant difference between RG and RB when fruits are at different maturity stages, as can be seen from Figures 4a and 4b. By setting different thresholds, fruit maturity can be judged. In addition, in real bayberry orchards, the harvest season usually lasts less than 20 d/year. During this period most bayberries are ripe enough to be picked. Even unripe fruit is picked and used to make wine or drinks. The identification of bayberry maturity is not the focus of this study, so it is not discussed in detail.

To reduce the interference of background noise, median filtering, and morphological opening operations were used for smoothing. The flood fill algorithm (FFA)[18] was used to fill the holes in the binary image of the fruit foreground area to compensate for the lack of pixels in the local area of the fruit segmentation caused by poor lighting and realize the potential of the fruit. The foreground area was accurately extracted. In the orchards' natural environment, the shooting background is complicated. To further reduce the interference of the background region similar to the fruit color characteristics such as yellowing branches, soil, weeds, the distance transformation[19], and watershed transformation methods[20] were combined to estimate the region of a single bayberry fruit. The prior knowledge of fruit shape was used to discriminate the fruit area and realize the denoising processing of the bayberry fruit foreground area.

Assuming that the target area in the fruit foreground area mask image is ω, calculate the distance image between pixel point p in ω and pixel point in the background area $\bar{\omega}$. The distance calculation expression is

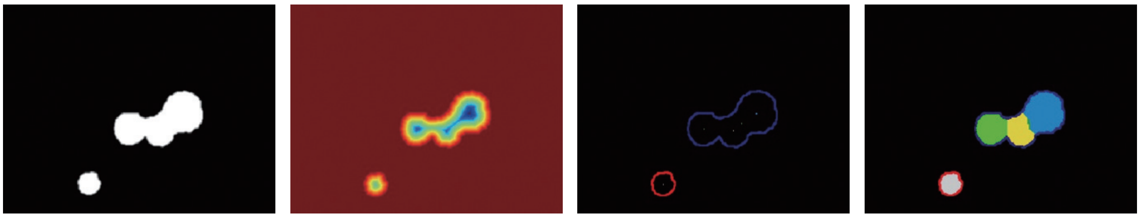
$$D(p) = \min \|p - \bar{\omega}\| \tag{8}$$

According to Figure 5, the larger the minimum distance between a pixel in the fruit area and the pixel in the background area in the image, the farther the pixel point is from the nearest background pixel, and vice versa. Therefore, to locate the center position of each fruit, the maximum value filter is used to solve the local maximum point M in the distance image. Furthermore, to extract a single target area in the foreground area, the solved local maximum point M is used as the marked seed point of the potential position of the fruit, combined with the marker-controlled watershed transformation, to realize the segment of the single fruit in the overlapping fruit area (as shown in Figure 5). Then, to restore as many single fruits as possible, the convex hull operation[21] is used to achieve region estimation. Since the bayberry fruit can be approximated as a circle and the shooting distance is controlled within the picking range of the robot, the separated fruit area can be distinguished based on prior knowledge of the shape and area of the bayberry fruit; that is, the area and circle of each separated fruit are calculated by setting the area and roundness thresholds, and the irregularly shaped background interference area is eliminated. Meanwhile, the bayberry fruit segmentation effect is improved. The calculation equation for fruit roundness is as follows:

$$\rho = \frac{4\pi S}{L^2} \tag{9}$$

where, S is the area of the fruit area; L is the perimeter of the fruit area.

Because the bayberry image collection distance is approximately 20-80 cm, the area value of the bayberry fruit area in the image falls within a certain range, and the bayberry fruit shape is mostly nearly circular, which can be clearly distinguished from the background area. To obtain a reasonable value range of the bayberry fruit areas and roundness threshold, based on prior knowledge of bayberry fruit, statistical analysis and calculation of the existing image data was carried out. First, 50 images in the data set were randomly extracted, and manual labeling was used to extract individual fruit regions in these images to obtain a total of 97 single-fruit binary images. Then, the area and roundness of bayberry fruits in all images were calculated (as shown in Figure 6), and the area distribution map and the roundness distribution map of the bayberry fruit area were obtained (as shown in Figure 7). It can be seen from Figure 7a that, except for the three abnormal values, the area of bayberry fruit is mainly distributed in the interval [200, 5600], so the maximum value of the area of bayberry fruit area can be set to 5600, and the minimum threshold value can be set to 200. Figure 7b shows that the roundness of bayberry fruit is mainly distributed in the interval [0.60, 0.95], so the fruit roundness threshold can be set to 0.60.



a. Foreground region mask b. Distance map c. Markers d. Segmented mask

Figure 5 Potential areas separated flowchart of bayberry

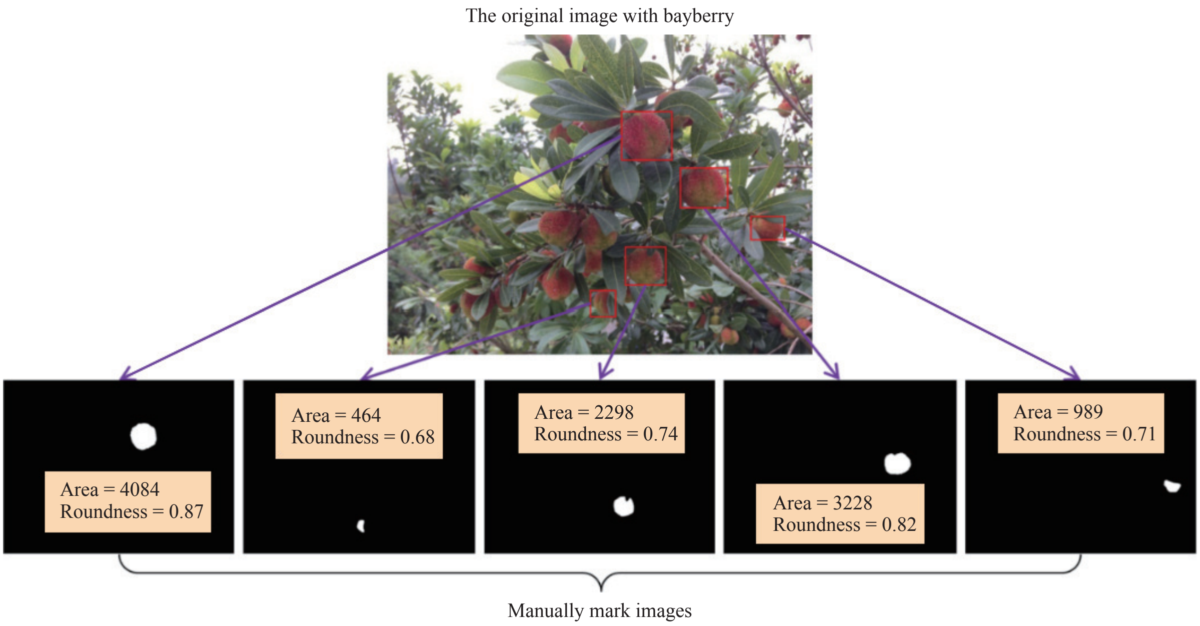
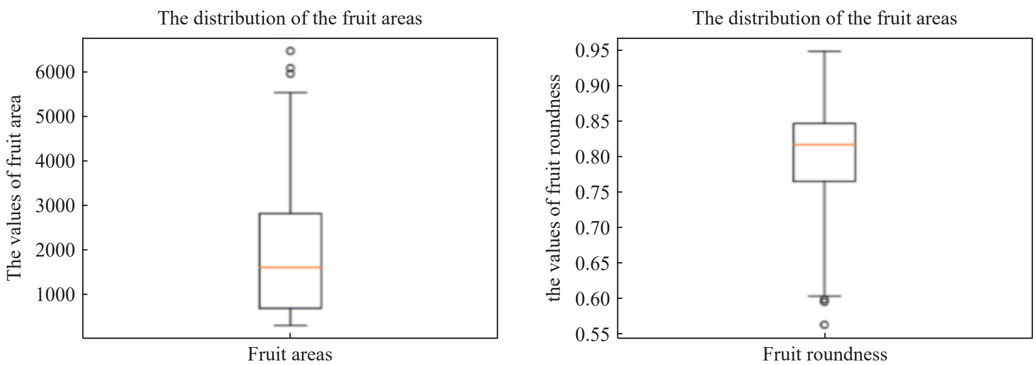


Figure 6 Examples of different bayberry areas and roundness



a. Distribution of the fruit areas b. Distribution of the fruit roundness

Figure 7 The distribution of the fruit areas and roundness

A detailed description of the bayberry segmentation algorithm process is as follows:

Algorithm: Bayberry fruit segmentation algorithm

Input: RGB image containing bayberry;

Output: Binary map of the fruit foreground area;

Step 1: Separate the RGB image into R, G, and B component images;

Step 2: Calculate the RG and the RB color difference map according to Equation (5);

Step 3: Calculate the binary map of bayberry foreground area according to Equation (6);

Step 4: Median filtering and morphological opening operation;

Step 5: Use FFA for hole filling;

Step 6: According to Equation (8), carry out distance transformation on the mask image of fruit potential area;

Step 7: Use marker-controlled watershed transformation algorithm to separate fruits;

Step 8: Use convex hull operation to estimate the shaded area of a single fruit;

Step 9: Calculate the area and roundness of each fruit area and eliminate the background interference area through the area and roundness threshold.

3 Experimental results and analysis

3.1 Analysis of experimental results

3.1.1 Local adaptive image enhancement

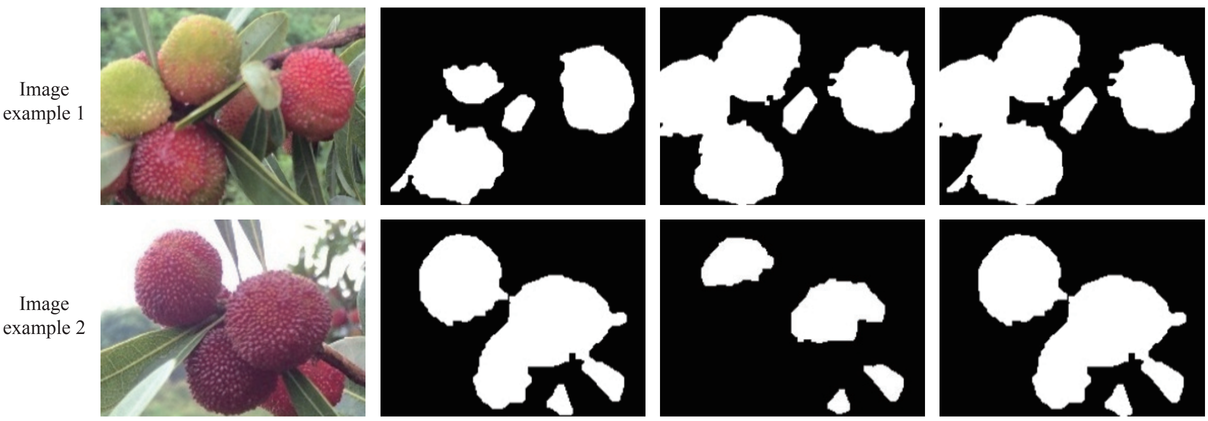
As shown in Figure 8, the bayberry images under three lighting conditions in the natural environment of the orchard (Figure 8) are subjected to image enhancement processing. One group of image examples was directly processed by CLAHE, and the other group of image examples was processed by LAIE. It is easy to see that rich local texture details can be obtained directly using the CLAHE method, but some areas are slightly exposed. Exposure slightly changes the color and texture information of the bayberry. However, more bayberry information is obtained by image enhancement based on the YUV space Y component and CLAHE. Especially for images with uneven local illumination and dark images, it has a more noticeable effect and overcomes the problem of excessive image noise amplification.

3.1.2 Bayberry fruit segmentation

For the image after illumination compensation, the RB color difference map is based on Otsu's thresholding[22,23], and the RG color difference map[24,25], and this study is used. The foreground region segmentation algorithm extracts the fruit region, as shown in Figure 9. It is easy to see that the RB color difference map can better segment yellow-green fruits, and the performance is poor in the segmentation of deep red ripe fruits. The RG color difference map can better segment ripe red fruits, but it is difficult to achieve yellow-green fruit segmentation. This study proposed a segmentation algorithm that combines the respective advantages of the RB color difference map and the RG color difference map and has a good segmentation effect for fruits of different colors at each stage. At the same time, as shown in Figure 10, the single target area processed by the watershed transformation algorithm controlled by the marker is marked with different colors. When the overlapped bayberry is separated, the fruit's outline is changed to a certain extent, and most of the occluded fruits are missing. To restore the fruit shape as much as possible, the convex hull operation can fill the missing area to a greater extent. Therefore, the target fruit area, size, and shape can be accurately located, and the bayberry fruit can be accurately identified through the area and shape.

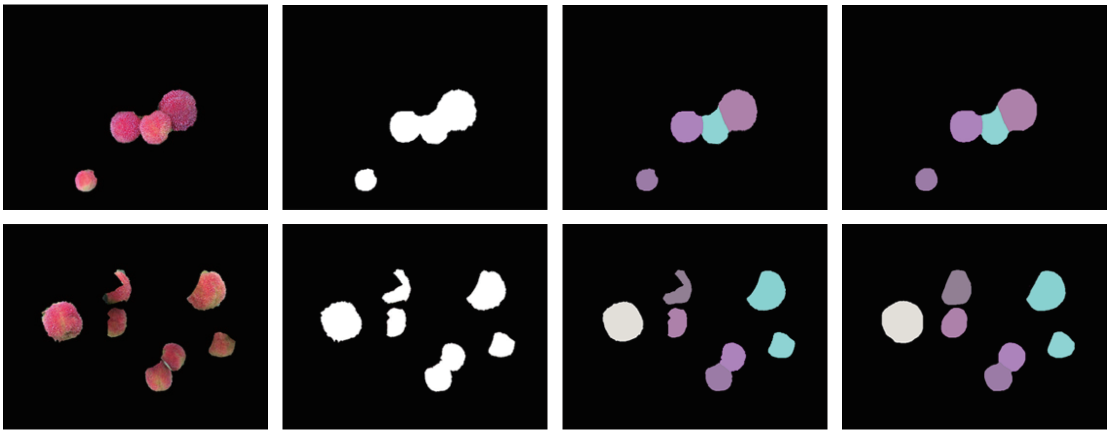
a. Image example 1 b. Image example 2 c. Image example 3

Figure 8 Bayberry image mage enhancement examples



a. RGB images b. Otsu-based RG color difference segmentation images c. Otsu-based RB color difference segmentation images d. Segmentation images of the proposed method

Figure 9 Bayberry image segmentation results examples



a. Segmented fruit regions b. Binary images of segmentation regions c. Use of markers to control the watershed transformation images d. Images after convex hull operation

Figure 10 Bayberry image postprocessing examples

3.2 Performance evaluation of bayberry fruit segmentation

To further verify the effectiveness of the algorithm, the bayberry fruit segmentation performance was quantitatively and objectively evaluated using accuracy (Acc), precision (Pc), recall (Rc), F1-score (F1), specificity (Sp), and mean intersection-over-union (M-IoU)[26,27] as evaluation indicators to measure the pros and cons of the algorithm. The evaluation index calculation formula is shown in Equations (10)-(16):

$$\mathrm{Acc} = \frac{\mathrm{TP}+\mathrm{TN}}{\mathrm{TP}+\mathrm{FP}+\mathrm{FN}+\mathrm{TN}} \tag{10}$$

$$\mathrm{Pc} = \frac{\mathrm{TP}}{\mathrm{TP}+\mathrm{FP}} \tag{11}$$

$$\mathrm{Rc} = \frac{\mathrm{TP}}{\mathrm{TP}+\mathrm{FN}} \tag{12}$$

$$\mathrm{F1} = 2\times\frac{\mathrm{Pc}\times\mathrm{Rc}}{\mathrm{Pc}+\mathrm{Rc}} \tag{13}$$

$$\mathrm{Sp} = \frac{\mathrm{TN}}{\mathrm{TN}+\mathrm{FP}} \tag{14}$$

$$\mathrm{IoU} = \frac{\mathrm{A}_{\mathrm{Inter\ section}}}{\mathrm{A}_{\mathrm{GT}}+\mathrm{A}_{\mathrm{SEG}}-\mathrm{A}_{\mathrm{Inter\ section}}} \tag{15}$$

$$\text{M-IoU} = \frac{\sum_{i=1}^{N}\mathrm{IoU}_i}{N} \tag{16}$$

where, TP is a true-positive example, that is, the number of fruit pixels that are correctly segmented; FP is a false-negative example, that is, the number of incorrectly segmented fruit pixels; TN is a true-negative example, that is, the number of nonfruit pixels that are correctly segmented; FN is a false-positive example, that is, the number of nonfruit pixels that are incorrectly segmented; A_{GT} is the area of the actual bayberry fruit region in the image; A_{SEG} is the area of the segmented bayberry fruit region, and $A_{\mathrm{Intersection}}$ is the area of intersection between the natural bayberry fruit and the segmented fruit. N is the number of IoU.

To better carry out the experimental analysis, some typical fruit segmentation methods are exploited for comparative evaluation, including the saliency target segmentation algorithm based on manifold ranking[10] (named MR-SOD), RB color difference map[22,23], RG color difference map[24,25] segmentation algorithms based on Otsu's thresholding (named RG and RB, respectively), and the 2R−G−B color difference method based on morphology and threshold (named 2R−G−B). At the same time, to evaluate the illumination compensation performance of the LAIE module, the proposed method is compared and quantitatively evaluated in the two cases where the LAIE module is not used, and the LAIE module is used. The comparison between the proposed method and the above four methods is listed in Table 1.

Table 1 Comparision of performance test results of differtents algorithms

Algorithm	Average detection time/s	Precision (Pc)	Recall (Rc)	F1-score (F1)	M-IoU	Accuracy (Acc)	Specificity (Sp)
MR-SOD	3.951	0.812	0.429	0.562	0.394	0.932	0.986
RB	0.076	0.648	0.907	0.756	0.604	0.941	0.943
RG	0.075	0.818	0.756	0.786	0.642	0.960	0.982
2R-G-B	0.078	0.778	0.849	0.812	0.674	0.962	0.973
The proposed method without LAIE	0.115	0.823	0.857	0.840	0.719	0.969	0.980
The proposed method with LAIE	0.136	0.855	0.906	0.880	0.731	0.974	0.983

First, only consider the comparison between the proposed method without the LAIE module and other methods. It can be seen from Figure 11 and Table 1 that MR-SOD can segment the fruit regions that are significantly different from the background and have significant target visual features. Meanwhile, it introduces less noise, but the fruit regions' segmentation is incomplete when the background is more complex, especially the yellow-green fruits that are similar to the background characteristics. Compared with MR-SOD, the proposed method still increases the recall rate by 42.8% when the precision is better. The completeness of the segmentation results is far better than that of the MR-SOD algorithm. RB and 2R-G-B can better segment the bayberry fruit area, but it is easy to introduce background noise interference. RG can segment ripe red bayberry fruit well, but it is challenging to achieve yellow-green fruit segmentation. RB has achieved a good recall rate, but the precision, F-score, and M-IOU of this proposed method are 17.5%, 8.4%, and 11.5% higher than those of RB, which shows that the overall performance of this proposed method is much better than RB. RG and 2R-G-B have a relatively balanced performance in precision and recall, but the proposed method still outperforms the above two methods in all indicators except real-time performance, in which the F1-score is 5.4% and 2.8% higher, respectively, and M-IoU is 7.7% and 4.5% higher, respectively. In terms of accuracy and specificity, all the methods performed well, and the indicators were all over 93.0%. Meanwhile, the method proposed in this paper achieves good balance and advanced performance with 96.9% and 98.0% results, respectively.

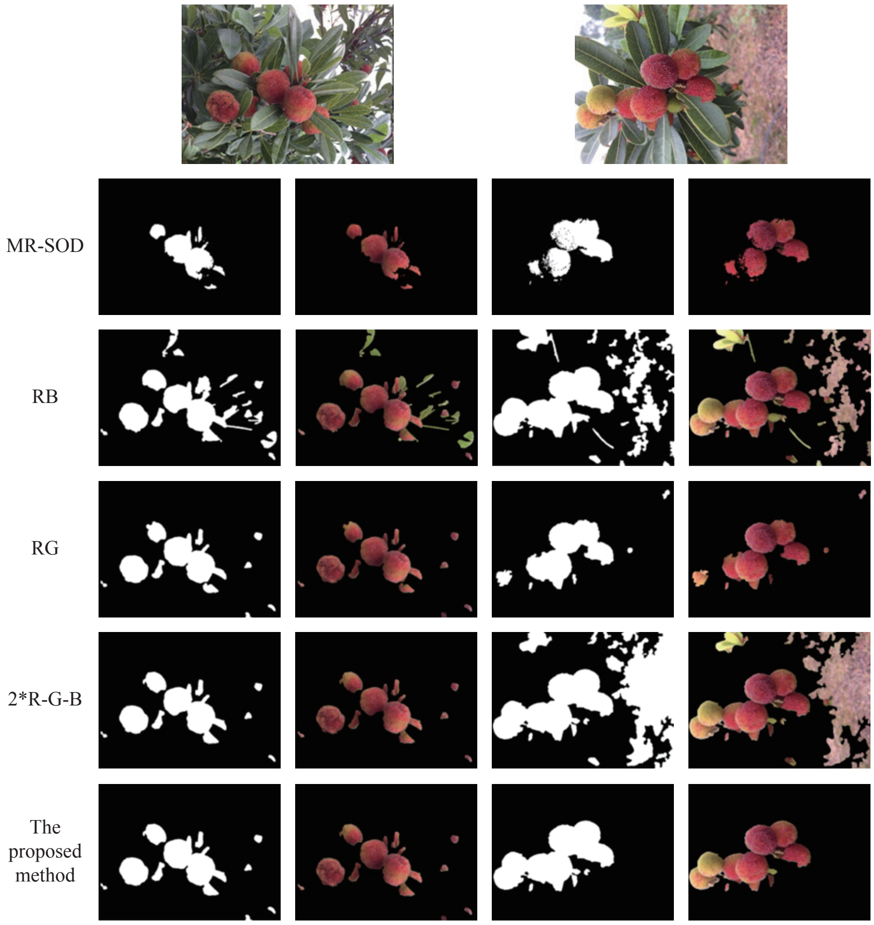


Figure 11 Visualization of the comparison experiments

Second, ablation experiments were carried out in two cases: using the LAIE module and not using the LAIE module (as listed in Table 1). After using the LAIE illumination compensation module, all the proposed method indicators are improved to a certain extent. The accuracy, recall, and F1-score are increased by 3.2%, 4.9%, and 4.0%, respectively, which improves the applicability and reliability of Bayberry segmentation in orchard environments.

In addition, the average detection time of the algorithm in this paper is 0.136 s, which is far less time-consuming than MR-SOD and is only approximately 0.060 s longer than RB, RG, and 2R-G-B. It has strong real-time performance. Therefore, it is easy to see that the proposed method can significantly reduce the influence of complex background interference, such as branches leaves, and land, in the orchard environment while ensuring real-time performance, and improving the segmentation effect of bayberry in the natural environment of the orchard. It has strong practicability.

4 Conclusions

To estimate the yield of bayberry fruits and automatically identify and pick them in the natural environment of agriculture, a method of automatic locating and segmentation of bayberry fruits based on machine vision in an orchard environment was designed. This method has strong robustness and applicability and can be used for bayberry yield estimation, automatic picking, and locating. It provides new insight into fruit segmentation and detection.

1) By the image enhancement method, which was based on the Y component and CLAHE in the YUV color space, the original images are enhanced, and the influence of illumination noise on the image quality is reduced;

2) An adaptive color difference segmentation for bayberry fruits with different colors was proposed. The proposed method can extract a more accurate foreground area, effectively avoiding complex background interferences such as branches, leaves, land, and weeds in the background;

3) According to the area and shape characteristics of the fruit, a single fruit location and shape calculation method based on watershed transformation and convex hull theory was proposed. The interference area was filtered out through the shape characteristics of the fruit, which improved the accuracy of bayberry segmentation;

4) The effectiveness of the proposed method was verified by experiments with actual scene data. It can effectively detect and segment bayberry fruits in the natural environment of orchards. The accuracy is 97.4%, the precision is 85.5%, the recall is 90.6%, and the M-IoU is 73.1%.

Although this proposed method can achieve higher segmentation accuracy while also maintaining a certain degree of real-time performance compared to previous methods, there are still several limitations that need to be further studied and solved in future work, such as improving the segmentation accuracy of complex scenes with severe occlusion and fruit cluster growth and evaluating fruit maturity grading. It is expected that through further optimization of the algorithm and the construction of deep learning models, it will be possible to solve the above limitations, improve the adaptability and reliability of the algorithm in real and complex environments, and promote the application of agricultural automatic picking technology.

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