Citrus recognition in real scenarios based on machine vision



Reconocimiento de cítricos en escenarios reales basado en visión artificial

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RESUMEN

- En la actualidad, los cítricos se cosechan principalmente de forma manual, con una baja eficiencia y un alto coste, lo que da lugar a una demanda inminente de robots para la recolección de fruta. Por lo tanto, reconocer y localizar cítricos de características complejas utilizando la tecnología de visión artificial es la premisa y la tecnología clave para que los robots puedan cosecharlos. Para reconocer de forma precisa e inmediata los cítricos maduros, este estudio propone un método novedoso basado en el método Otsu de umbral adaptativo y en el método mejorado del anillo aleatorio. En primer lugar, una agrupación de cítricos fue segmentada utilizando el método Otsu de umbral adaptativo, sobre el componente V del espacio de color Crominancia de Luminancia (YUV), extrayendo después, la agrupación real de cítricos tras un proceso de eliminación del ruido. En segundo lugar, el contorno de los cítricos fue extraído usando un operador de detección de Canny con el punto de catástrofe de curvatura removido. El borde menor de los cítricos se colocó sobre la imagen para obtener el borde de los cítricos de cada segmento. Por último, el anillo de características de los cítricos se ajustó para cada segmento a un borde continuo utilizando el método mejorado de anillo aleatorio basado en el algoritmo Greedy. Se realizaron experimentos utilizando las imágenes de los cítricos en varios escenarios reales. Los resultados demuestran que el método propuesto aumenta la tasa global de reconocimiento de los cítricos al 95% con un consumo de tiempo de aproximadamente 80 ms. El método propuesto mejora la eficiencia del reconocimiento, aumenta la precisión del reconocimiento de los cítricos y proporciona apoyo técnico a los robots recolectores de fruta. Por último, el método propuesto puede generalizarse a la localización y el reconocimiento de otras frutas similares, lo que proporciona un valor de investigación significativo.
- **Palabras clave:** Reconocimiento de cítricos, método Otsu de umbral adaptativo, algoritmo Greedy, método del anillo aleatorio.

ABSTRACT

At present, citrus is mainly harvested manually with low efficiency and high cost, thereby resulting in an imminent demand for fruit-harvesting robot. Hence, recognizing and locating citrus from complex backgrounds using machine vision technology is the premise and a key technology for robots to harvest them. To accurately and immediately recognize mature citrus, this study proposes a novel method based on the Otsu adaptive threshold method and on the improved random ring method. First, a citrus region was segmented using the Otsu adaptive threshold method overthe V component of the Luminance Chrominance (YUV) color space, extracting then the real citrus region after undergoing a denoising processing. Second, the citrus edge was extracted using a Canny detection operator with the curvature catastrophe point removed. The short citrus edge was placed in the background to obtain the citrus edge of each segment. Lastly, the citrus feature circle was fitted for continuous citrus edge in each segment using the improved random ring method based on the greedy algorithm. Experiments were conducted using the citrus images in various real scenarios. Results demonstrate that the proposed method increases the overall recognition rate of citrus to 95% with time consumption of approximately 80 ms. The proposed method improves the recognition efficiency, enhances the accuracy of citrus recognition, and provides technical support for fruit-harvesting robots. Lastly, the proposed method can be generalized to the location and recognizition of other similar fruits, thereby providing significant research value.

Keywords: Citrus recognition, Otsu adaptive threshold method, Greedy algorithm, Random ring method.

1. INTRODUCTION

Citrus harvesting is characterized by strong seasonality, complex operation, high labor intensity, and low efficiency. A survey indicated that the labor used in citrus harvesting operation accounts for 33% to 50% of the labor used in the entire production process [1]. At present, the traditional method of manual labor is dominant for the majority of the citrus harvesting process and has a unique advantage in the identification of fruits and reduction of fruit damage. However, manual harvesting is labor-intensive but the picking efficiency is low. Given the rapid advancements in urbanization construction, the current rural labor force is considerably short in supply and the cost of artificial harvesting continues to increase. To reduce cost and improve efficiency, citrus harvesting robots should be developed. The use of machine vision technology to accurately and immediately recognize citrus in real scenarios from complex backgrounds is necessary for robots to successfully accomplish citrus harvesting. Fruit recognition is the key technology for the robots to harvest fruits. If a robot wants to harvest citrus accurately and rapidly, then it should be able to accurately identify and locate the citrus. At present, citrus recognition technology mainly identifies citrus from the background by

using conventional image processing or deep learning. Evidently, for mature citrus in real scenarios, citrus images are easily affected by many external factors such as various illumination conditions, complex environment (i.e., foliage occlusion or fruit overlap), which can reduce the recognition accuracy of citrus. Nowadays, deep learning techniques are the commom approaches used in fruit fertures extraction for machine learning [2]. The preceding methods has not been widely used because the conventional image processing methods generally have low recognition rates for citrus with high overlap or occlusion , and the deep learning techniques require higher computer hardware. To recognize mature citrus in the complex environment, an image recognition method should be developed to improve the recognition accuracy and efficiency of citrus harvesting.

2. STATE OF THE ART

At present, numerous domestic and foreign studies on fruit recognition have been conducted. Current fruit recognition methods based on conventional image processing algorithms can deal with complex environment such as: Liu et al. designed a depth-sphere ball interception method for citrus recognition, in which the recognition rate of isolated citrus is 97.8%, although the recognition rate in the touch area is 76%. Moreover, the recognition rate of citrus in the complex environment is only 63.8% [3]. By using the K-means clustering algorithm and hough transform circle detection method, the fruit recognition rate has been increased to 85% in the complex environment [4]. Cai et al. used Ostu algorithm to segment the images of mature oranges and background, although they only discussed overlapping fruits [5]. Lv et al. segmented shielded and overlapping citrus using the watershed algorithm and repaired the occlusion region using the convex hull algorithm, thereby resulting in a recognition rate of 80% [6]. Rakun et al. identified apples by combining color, texture, and three-dimensional shape features, although the extraction of multiple features leads to more calculation time [7]. Ghabousian and Shamsi segmented apple color images by using the fuzzy clustering algorithm, but the program also took a lot of time [8]. Kelman and Linker applied the convexity test to detect apples, although this method resulted in considerable recognition error for the image of occluded apples [9]. Wang et al. combined the K-means normalized cut algorithms to segment uncovered and overlapping apples, although the recognition rate is high, such result was only for the double overlap situation in real scenarios [10]. Sun et al. employed a filtering model to identify citrus with a recognition rate of 86.7% [11]. Some fruit recognition methods can deal with real illumination changes using multi-feature fusion such as: Lak et al. applied edge detection and segmented a red apple image under natural light conditions combined with color and shape features, thereby resulting in a recognition rate of 83.33% [12]. Arefi et al. combined the Red Green Blue(RGB), Hue Saturation Intensity (HSI), and Luminance In-phase Quadrature-phase (YIQ) color spaces to extract the characteristics of mature tomatoes [13]. However, this method is only suitable for greenhouse lighting condition. Given the change of illumination and the existence of occlusion, the color properties of target objects within natural citrus-grove scenes under various light conditions were analyzed, and a preliminary segmentation was put forward by fusing the chromatic aberration information and normalized RGB model [14]. However, this method is computationally complex and unsatisfactory for restoring fruit surface.The work presented a method that employs visible spectrum cameras for robust grape berries recognition and grape bunch detection that does not require artificial illumination nor is limited to red or purple grape varieties. The proposed method relied on shape and texture information together with a strategy to separate regions of clustered pixels into grape bunches, and grapes bunches were detected with an average precision of 88.61% [15]. Few classical computer vision algorithms can deal properly with real field scenarios, and a novel image processing algorithm based on candidate hot-spot detection in combination with statistical inference methods was proposed to tackle wheat disease identification successfully in wild conditions [16]. At present, some considerable fruit recognition methods used neural networks or even deep learning techniques to deal with complex environment: Jia et al. designed an apple recognition method based on combining K-means clustering segmentation with genetic radial basis function (RBF) neural network , and the recognition rate can reach 95.38% and 96.17% for covered fruit and overlapping fruit, respectively. But the program also took a long training time [17]. Bi et al. proposed a citrus recognition based on deep convolutional neural network, which is suitable for citrus images with low occlusion degree and has a short consuming time [18]. Wang et al. proposed a apple recognition method based on region-based fully convolutional network (R-FCN) , and the recognition_accuracy rate can reach 95.2% . However, the average recognition time was 187ms per image and the structure of R-FCN model was too complex [19]. Fu et al. designed a kiwifruit image recognition system based on the convolutional neural network (CNN). The overall recognition rate of the CNN model can reache 89.29% and it took a time of 270ms in average to recognize a fruit [20]. Zhou et al. proposed a tomato organs recognition method based on deep convolutional neural network (DCNN), in which the detection average precisions for the fruit, flower and stem were 81.64%, 84.48% and 53.94%, respectively [21]. Bresilla et al. presented an approach for fruit detection based on state-of-the art deep neural networks techniques using single shot detectors as a convolutional neural network (CNN) to detect fruits of apple and pears in the tree canopy, and the detect accuracy can reach to 95%. However the corresponding platform was the compute power needed for the system to run [22].The preceding studies are primarily for a single fruit or for overlapping fruits with low degree of occlusion. Meanwhile, compared with the traditional computer vision algorithms, the deep learning techniques such as various convolutional neural networks need more training images. Given the complicated overlap or leaf occlusion under real scenarios, the current study analyzes the citrus recongnition methods in complex environment to improve the recognition rate, particularly by shortening the time consumption and improving the recognition efficiency. This study extracts the citrus region using the YUV color space and Otsu adaptive threshold method. Thereafter, the curvature value is applied to separate the citrus edge and an improved random ring method based on the greedy algorithm is used to fit the citrus contour. These processes are combined with the citrus images in complex en to verify the recognition effect of the proposed method.

The rest remainder of this study is organized as follows.In section 3, Otsu adaptive threshold method is presented and the detailed processes of the marginal curvature method and the improved random ring method are given successively. In Section 4, Experiments are conducted using the citrus images in various real scenarios and results are analyzed and discussed. Finally,the conclusions of this study were drawn in Section 5.

3. METHODOLOGY

The proposed method includes three processing modules: real image acquisition, citrus region extraction, and citrus target recognition. The steps are shown in Fig.1.

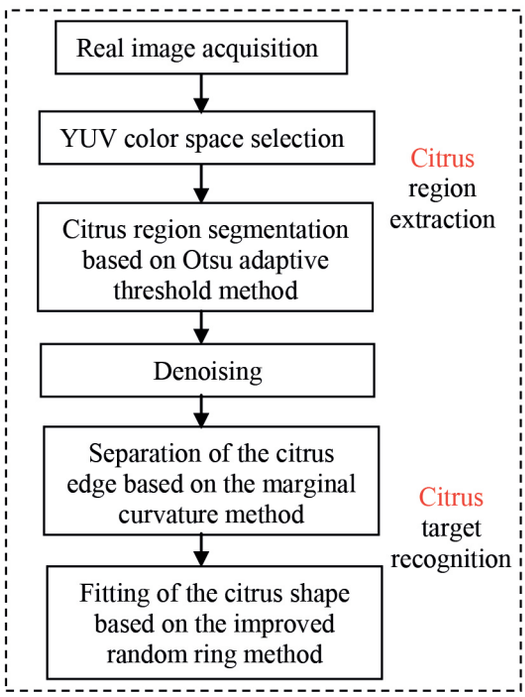
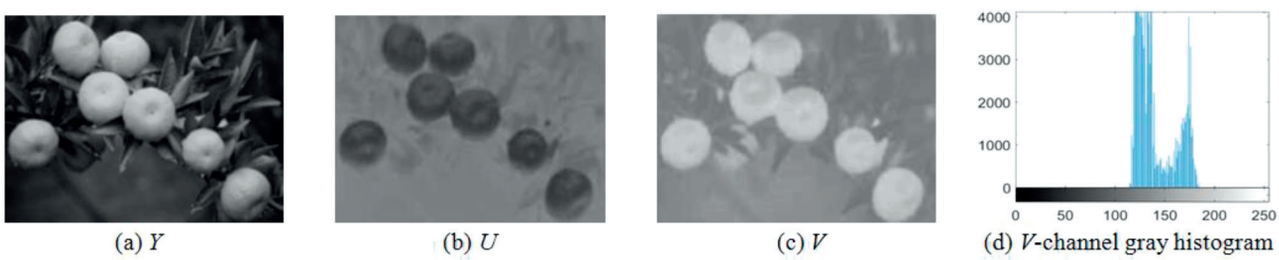


Fig. 1: Steps for citrus recognition

To avoid the influence of light intensity on citrus recognition, the U and V components in the YUV color space are analyzed. Upon using the Gaussian filter of multiple citrus images in a real scenario and comparing the images of the U and V channels, the chromatic aberration between the citrus and background in the V channel was determined to be larger than in the U channel. Therefore, the V component of the YUV color space is used for image segmentation. Fig. 2 shows the images separated from the Y, U, and V channels and the V-channel gray histogram.

3.1.2. Citrus region segmentation

The common segmentation methods include the Otsu threshold method and K-means clustering algorithm. The one-dimensional Otsu threshold method has a satisfactory segmentation effect with good real-time performance and rapid calculation speed. The K-means clustering algorithm is an unsupervised learning algorithm that is appropriate for processing spherically distributed data. The Otsu threshold method and K-means clustering algorithm are effective for segmenting the target region of citrus image in a real scenario. However, the Otsu adaptive threshold method takes substantially less time than the K-means clustering algorithm [25]. Hence, the Otsu adaptive threshold method is used to segment citrus region and its principle is presented as follows: The gray level of an image is [*0, L-1*], where the number of gray scale is L. If the segmentation threshold is t, then the image can be divided into the target region E and background region F. With the gray scale [*0, t*] in region E and the gray scale [*t*+1, L-1] in region F, the probability and gray mean of the two regions are calculated in the following formulas.



(a) Y (b) U (c) V (d) V-channel gray histogram

Fig. 2: Citrus image in the YUV color space. (a) The Y component in the YUV color space.(b) The U component in the YUV color space.(c) The V component in the YUV color space.(d)The V-channel gray histogram

3.1. CITRUS REGION EXTRACTION

When citrus are recognized in real scenarios, they should be separated from the background and the noise and non-target regions should be removed during the extraction process.

3.1.1. YUV color space selection

In a real scenario, an evident color contrast exists between a mature citrus and surrounding environment. This study applies the YUV color space to extract the citrus region, where Y is the luminance and U and V are the chrominance to describe the image color and saturation. The YUV color space separates the brightness from the color, thereby making it more suitable for the change of illumination intensity than the RGB color space. Moreover, the YUV color space can be obtained through the linear transformation from the RGB color space, i.e., no overflow that will cause image information loss [23].The conversion relationship between the RGB and YUV color spaces is as follows [24]:

$$\begin{bmatrix} Y \\ U \\ V \end{bmatrix} = \begin{bmatrix} 0.299 & 0.587 & 0.114 \\ -0.148 & -0.289 & -0.437 \\ 0.615 & 0.515 & -0.100 \end{bmatrix} \times \begin{bmatrix} R \\ G \\ B \end{bmatrix} \quad (1)$$

$$\omega_0 = \sum_{i=0}^{t} P_i \quad (2)$$

where ω_0 is the target region probability.

$$\omega_1 = \sum_{i=t+1}^{L-1} P_i \quad (3)$$

where ω_1 is the background region probability.

$$\mu_0 = \sum_{i=0}^{t} \frac{ip_i}{\omega_0} \quad (4)$$

where μ_0 is the gray mean in the target region.

$$\mu_1 = \sum_{i=t+1}^{L-1} \frac{ip_i}{\omega_1} \quad (5)$$

where μ_1 is the gray mean in the background region.The probability of occurrence for the pixels of the gray level i is P_i and $\omega_0 + \omega_1 = 1$.

The maximum inter-class variance formula indicates that the maximum inter-class variance σ^2 of the target and background regions is as follows:

$$\sigma^2 = \omega_0(\mu_0 - \mu)^2 + \omega_1(\mu_1 - \mu)^2 \quad (6)$$

where $\mu = \omega_0\mu_0 + \omega_1\mu_1$, μ is the gray value mean of the entire image. When σ^2 obtains the maximum value, the corresponding threshold t is the optimal threshold. The citrus region segmented with the Otsu adaptive threshold method for Fig. 2(c) is shown in Fig. 3 (supplementary material).

3.1.3. Denoising

Fig. 3 shows that citrus is separated from the background, but the image contains such noises as void, burr, and small region. The following steps are undertaken to eliminate such noises. First, the small region is removed by eroding first and dilating later for morphology and the cavity is recovered using seed filling method. Second, a threshold is set according to the area characteristics of the citrus region. When the area of a single connected region is smaller than the threshold, unary complement should be made for all the pixels in the region, and vice versa. Lastly, the citrus edge smoothing is performed and the citrus region after being denoised is shown in Fig. 4 (supplementary material).

3.2. CITRUS TARGET RECOGNITION

Citrus target recognition involves the separation of citrus edges and the fitting of citrus shapes. After the citrus region is extracted, the citrus is separated from the background, while the center and radius of each citrus should be determined to determine the size of each citrus region. In a real scenario, the citrus image will be partially overlapped, stuck, or occluded. Therefore, the marginal curvature method is used to separate the citrus edges, followed by an improved random ring method based on greedy algorithm to fit the feature circle of the citrus shape.

3.2.1. Separation of the citrus edge

The citrus edge is extracted from Fig. 4 using a Canny detection operator. Given the overlapping or occlusion, the overlapping parts should be separated into the edges of the single citrus or to eliminate some interfering arcs (i.e., the so-called interfering arcs are the edges extracted for edge loss, increase, and distortion due to leaf occlusion and shadow, among others). The curvature of the same citrus edge point is the same. If the overlap occurs, then the curvature of the edge point at the junction of the overlapping edge will be mutated and the edge formed by leaf occlusion will also have similar features [26]. Hence, the citrus edges extracted can be separated using the change of the edge point curvature. The curvature is defined as follows [27]: The curvature k of any point A on the curve $y=f(x)$ is the change of the tangent angle along the curve direction. As shown in Fig. 5 (supplementary material), A and B are arbitrary two points on the curve.

$$k = \lim_{\Delta l}\left|\frac{\alpha_1 - \alpha_2}{\Delta l}\right| = \lim_{\Delta l}\left|\frac{\Delta\alpha}{\Delta l}\right| \quad (7)$$

where α_2 is the tangent angle of point A, Δl is the arc length of curve AB segment, α_1 is the tangent angle of point B and $\Delta\alpha$ is the angle of tangential change of curve segment.

The separation of the citrus edges is described as follows.

(1) The curvature of the adjacent edge point for the citrus region is calculated and a curvature change threshold is set. If the curvature change of an edge point is higher than the threshold, then the edge point is converted into the background. Otherwise, the edge point should be maintained. Thus, the overlapping citrus edges and disturbing arc segments can be separated.

(2) The processed edge points are disposed on the base of the connection rule. The points in the same connected region are regarded as the edge points of the same citrus. Otherwise, they belong to different citrus edge points.

(3) If the edge length of a segment is below the set threshold, it is considered an interfering arc without follow-up fitting. Otherwise, it is used for follow-up fitting. The citrus edges before and after separation are shown in Figs. 6 (a) and (b), respectively.

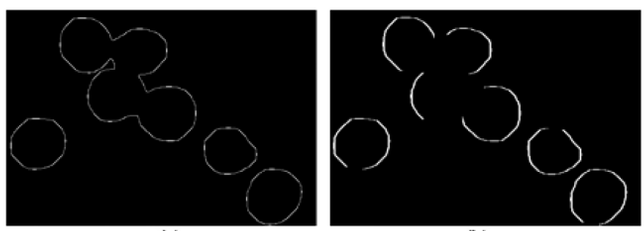


Fig. 6: Citrus edges before and after separation.(a)The citrus edges before separation.(b) The citrus edges after separation

3.2.2. Fitting of the citrus shape

After the entire or a certain edge of each citrus is extracted, it is considered a known edge to fit the citrus shape. This study applies an improved random ring method based on the greedy algorithm to fit the irregular circle of the citrus and find the center of the circle. If the majority of the points of the citrus edge fall into a circle, then the circle is defaulted as a feature circle of the citrus.

3.2.2.1. Standard random ring method

The standard random ring method indicates that if the majority of the points on the citrus edge fall into a circle, then the corresponding feature circle of this ring is defaulted as a fitted feature circle. This method is described as follows [28]: A feature circle is drawn numerous times for any non-collinear three points of the citrus edge. The center of the feature circle is $0(0_x, 0_y)$ and its radius is r. The random ring corresponding to the feature circle is obtained by adding or subtracting $w/2$ with radius r, where, w is called the width of the random ring. If any point of the citrus edge falls into the ring, then its coordinates (x, y) should satisfy the following inequality:

$$r - \frac{w}{2} \le \sqrt{(x - O_x)^2 + (y - O_y)^2} \le r + \frac{w}{2} \quad (8)$$

The number of pixels of the citrus edge in the ring is counted. The more pixels are included, the better the fitting effect. The steps in the standard random ring method are as follows.

Step 1: Create a data space V for all citrus edges, determine the width of ring w, and set the maximum number of cycles;

Step 2: Randomly take 3 points in space V. If the three points are collinear, then repeat Step 2. Otherwise, proceed to the next step;

Step 3: Solve the feature circle radius r of the three points and determine its center O then obtain the corresponding random ring. By this time, if the number of cycle is below the maximum number of cycle, then proceed to the next step. Otherwise, the algorithm ends;

Step 4: If the radius r is within the constraint range, then count the pixels of the citrus edge in the ring. If the pixels exceed 2/3 of the total pixels of the feature circle perimeter, then this feature circle is really the citrus feature circle and the algorithm ends. Otherwise, return to Step 2.

3.2.2.2. Improved random ring method

The standard random ring method randomly takes three points from space V. The initial and transformed feature circles are randomly generated, thereby leading to time-consuming procedure. Therefore, this study proposes an improved random ring method based on the greedy algorithm. The greedy algorithm is an optimal solution of stepwise construction, with the essence making a seemingly optimal decision for problem-solving. The steps of the improved random ring method are described as follows.

Step 1: To obtain a superior initial solution, a space V is created for each segment of the separated citrus edge (i.e., the arc) and selects the minimum and maximum values of the X and Y coordinates for each arc, i.e., the four points as $A(x_{min}, y_1)$, $B(x_{max}, y_2)$, $C(x_1, y_{min})$, $D(x_2, y_{max})$. The combination of any three points can produce three feature circles;

Step 2: For each feature circle, obtain the corresponding random ring and calculate the ratio of pixels of the citrus edge in the ring to the total pixels of the feature circle perimeter, then select the feature circle M corresponding to the maximum ratio m. This feature circle serves as an initial feature circle for follow-up calculation. Designate the maximum number of cycles $e=500$ and the number of cycles L is initialized to 1;

Step 3: If the selected points corresponding to the initial feature circle in step 2 are $A(x_{min}, y_1)$, $B(x_{max}, y_2)$, $C(x_1, y_{min})$, then randomly select two points from the three to transform its coordinates. To ensure the efficiency of transformation, the horizontal and vertical coordinates are transformed simultaneously, such as $A(x_{min}, y_1) \rightarrow A(x_{min} \pm \Delta, y_1)$, $B(x_{max}, y_2) \rightarrow B'(x_{max}, y_2 \pm \Delta)$, where Δ is a small positive random value . Thereafter, produce the feature circle of three points A', B',C and obtain the corresponding random ring, then calculate the ratio m' of the pixels of the citrus edge in the ring to the total pixels of the feature circle perimeter, thereby obtaining the variable h in the following formula:

$$h = \begin{cases} m & (m \geq m') \\ m' & (m < m') \end{cases} \tag{9}$$

Step 4: If $h>0.85$, then output the fitted feature circle at this point and return to Step 1 to perform the feature circle fitting of the next citrus edge. If $h \leq 0.85$, $L = L + 1$ and $L < e$, then return to Step 3. If $L = e$, then return to Step 1.



Fig. 7: Feature circles of fitting citrus edges

Note that if at least 70% overlaps for the feature circles fitted by the separated citrus edges, and the center distance is below a given threshold, then the separated citrus edges should be considered belonging to the same citrus. The feature circles of fitting citrus edges using the improved random ring method are shown in Fig.7.

4. RESULT ANALYSIS AND DISCUSSION

Given the dependence on the color difference for citrus region segmenting, the four common citrus varieties of Kiyomi, Navel orange, Ponkan, and Harumi are selected for the experiment to verify the adaptability of the proposed method. To recognize mature citrus in the complex environment, the unoccluded non-overlapping citrus (Fig. 8(a)), the occluded citrus (Fig. 8(d)), the unoccluded overlapping citrus (Fig. 8(g)), the overlapping shadowy citrus (Fig. 8(j)), and the occluded overlapping citrus (see Fig. 8(m)) are selected for experiments in different real scenarios. In this experiment, the computer used is a CPU Intel(R) Core(TM) i5-5200U, with 4.00 GB memory, Microsoft Windows 10, with MATLAB2016a programming. In Fig. 8, the first column shows the real citrus images (see Figs. 8(a), (d), (g), (j), and (m)), the second column presents the extracted citrus regions (see Figs. 8(b), (e), (h), (k), and (n)), and the third column shows the citrus recognition images (see Figs. 8(c), (f), (i), (l), and (o)).

A total of 60 citrus images in a real scenario are selected for the recognition experiments. Tables 1 and 2 show the experimental results. Table 1 shows that the Otsu adaptive threshold method can achieve the following segmentation accuracy: 100% for the target region of the non-overlapping citrus regardless of occlusion; 93.9% for the overlapping, unoccluded, or less occluded citrus; and 89.7% for the occluded overlapping citrus. Similar with the segmentation accuracy of the citrus region using the K-means clustering algorithm, the Otsu adaptive threshold method only takes 1 ms, which is considerably less than the 30 ms by the former.

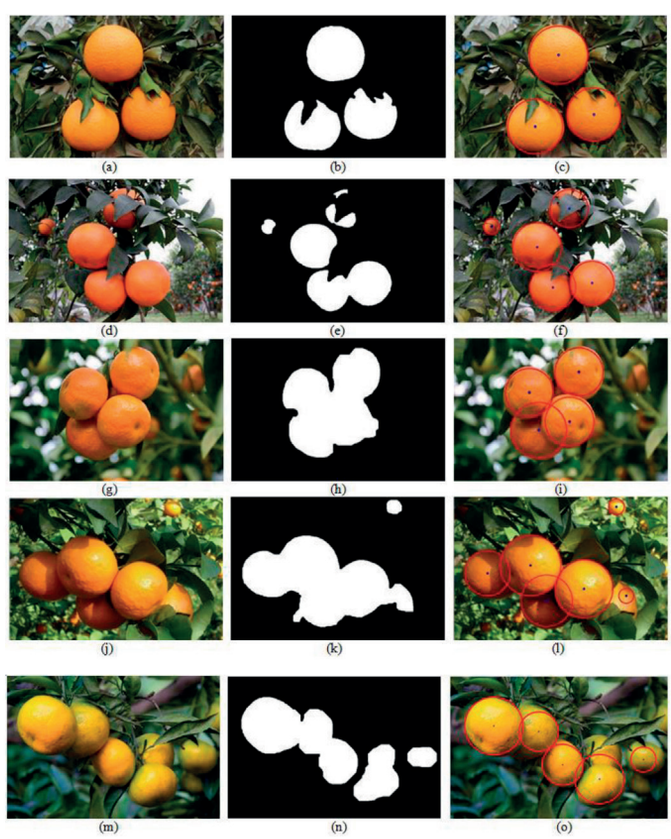


Fig. 8. Citrus recognition results. (a) (d) (g) (j) (m) The real citrus images. (b) (e) (h) (k) (n) The extracted citrus regions. (c) (f) (i) (l) (o)The citrus recognition images

Citrus status	Citrus number	k-means clustering algorithm	Otsu adaptive threshold method	Segmentation accuracy
The unoccluded non- overlapping citrus	47	47	47	100.0%
The occluded non- overlapping citrus	52	52	52	100.0%
the unoccluded overlapping citrus	82	77	77	93.9%
the occluded overlapping citrus	68	61	61	89.7%
Algorithm time consuming	--	30ms	1ms	--

Table I. Extraction results of citrus region

Citrus status	Citrus number	Standard random ring method	Improved random ring method	Recognition rate	
				Standard random ring method	Improved random ring method
The unoccluded non- overlapping citrus	47	47	47	100%	100%
The occluded non- overlapping citrus	52	44	52	84.6%	100%
the unoccluded overlapping citrus	82	59	75	72.0%	91.4%
the occluded overlapping citrus	68	46	59	67.6%	86.8%
Algorithm time consuming	--	329ms	23ms	--	--

Table II: Citrus recognition results

Comparison item	Literature [5]	Literature [6]	Literature [11]	Literature [18]	The proposed method
Recognition rate	95%	87.2%	86.7%	86.9%	95.2%
Procedure time consuming	--	1.5s	<100ms	80ms	80ms

Table III: Comparison of citrus recognition results

The experimental results in Table 2 show that the improved random ring method yielded a recognition rate of 100% for the non-overlapping citrus regardless of occlusion; 91.4% for the overlapping, unoccluded, or less occluded citrus, which is hardly sensitive to illumination; and 86.8% for the occluded overlapping citrus. Note that the mutation point is eliminated by the curvature and the overall recognition rate of the citrus is improved using the improved random ring method. Moreover, the process consumed 23 ms, which is considerably shorter than the 329 ms of the standard random ring method.

Tables 1 and 2 show that a certain misrecognition rate in the proposed method because of the following reasons:

(1) Under natural conditions, considerable illumination influencing factors, particularly backlight, reflection, and shadow, lead to an incomplete edge or information loss for the citrus region extraction. Consequently, the proposed method is unable to accurately recognize the complete citrus and even causes misrecognition.

(2) The substantially large overlapping or occlusion region (e.g., occlusion or overlapping region of over half of the citrus region) makes the citrus region considerably small. If the area of the citrus region is too small, the citrus region will be mistaken for noise to be removed or cause a large deviation between the fitted citrus feature circle and the actual citrus shape.

(3) Some citrus are far from the camera and can be mistaken for noise removal owing to the considerably small region displayed in the image.

(4) The target misjudgment or substantial difference between the extracted citrus edge and the actual citrus shape caused by citrus deformation will result in high misrecognition rate.

The proposed method is compared with the ones in the reference literature [5], [6], [11], and [18] for citrus recognition using 30 citrus images in the complex environment. Table 3 shows the experimental results.

The experimental results in *Table* 3 show that the overall citrus recognition rate of the proposed method is 95.2%, which is higher than that of the other methods. The total time consumption of the proposed method is 80 ms, which is faster than those of the other methods and equivalent to the recognition method in the literature [18].

5. CONCLUSIONS

Rapidly recognizing mature citrus from complex backgrounds in real scenarios using machine vision technology is the premise and key technology for citrus harvesting robots to complete their work. To solve the problem of poor recognition and low recognition efficiency caused by various states of mature citrus in the complex environment, this study first uses the *V* component and Otsu adaptive threshold method to segment citrus regions and eventually denoise data to determine these regions. Thereafter, edge separation is performed to obtain the citrus edges of each segment for fitting. Lastly, the citrus feature circle is fitted using an improved random ring method based on the greedy algorithm. The following conclusions are provided.

(1) The use of the *V* component in the YUV color space to extract the citrus region from the background can reduce the interference of illumination. The Otsu adaptive threshold method yields a minimum of 89.7% segmentation accuracy within 1 ms for the citrus region segmentation.

(2) When the citrus feature circle is fitted, the original citrus edges are separated into discrete arcs using the edge curvature method and the interfering arcs are eliminated through curvature mutation, which can effectively deal with overlap and occlusion. An improved random circular method based on the greedy algorithm is used to fit the citrus arc separately in segment. This process increases the accuracy of the fitting feature circle and substantially reduces the time consumption at a mere 23 ms.

(3) The citrus images collected in real scenarios are divided into four types: the unoccluded non- overlapping citrus, The occluded non- overlapping citrus, the unoccluded overlapping citrus, and the occluded overlapping citrus. Given

the increase of the citrus overlap rate and under strong reflection and backlight conditions, the recognition rate of the proposed method is gradually reduced, the overall citrus recognition rate remains up to 95.2%, and the total processing time is only 80 ms.

In proceeding from the substantial difference between the target fruit and background color, the proposed method focuses on the analysis of the complex state of citrus in real scenarios. Moreover, this study designs the corresponding method for citrus target extraction and recognition. Compared with other methods, the proposed method has higher recognition rate and shorter time, which can effectively recognize citrus in different real scenarios. Therefore, the proposed method can provide efficient and accurate image localization and recognition technology support for fruit harvesting robots and has important research significance and wide practical value. However, this method's shortcoming is that the citrus recognition rate should be generally improved for high overlap rate and occlusion. The next studies may focus on how to further reduce the noise interference in complex states and improve the recognition accuracy of the target region. Furthermore,our continuation of this study will include more images of different fruit species, at different growth stages, with different training systems, and a mobile platform for capturing those images.

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APPRECIATION

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SUPPLEMENTARY MATERIAL

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