Image segmentation algorithm for greenhouse cucumber canopy under various natural lighting conditions

Sun Guoxiang, Li Yongbo, Wang Xiaochan*, Hu Guyue, Wang Xuan, Zhang Yu

(*College of Engineering, Nanjing Agricultural University, Nanjing 210095, China*)

Abstract: In this study, machine vision technology was used to capture images of greenhouse cucumber canopy, and image segmentation was implemented under various natural lighting conditions. The images were enhanced by multi-scale retinex with color restore (MSRCR), and the MSRCR images were segmented by four algorithms: normalized difference index (NDI), excess green (ExG), modified excess green (MExG), and modified excess green minus excess red (MExG-ExR). The results indicated that compared with the original images, under various lighting conditions, the average evaluation indexes of brightness, information entropy, average gradient and mean gray value of the MSRCR images were increased by 38.71%, 8.04%, 4.54%, and 37.81%, respectively, and only the contrast degree decreased by 12.13%. The MExG-ExR segmentation algorithm was used to segment the MSRCR images (fifty images under various lighting conditions in the test and it performed best among the four segmentation algorithms, average overlap ratios and recognition rates of were 99.28% and 98.91%, respectively, while 38.39% and 37.95% respectively for original image. These results indicated that the MExG-ExR segmentation algorithm applied to a MSRCR canopy image produced the most stable results among the four algorithms. By using the MSRCR image enhancement algorithm, the interference of lighting on greenhouse cucumber canopy images was reduced and the foundation for achieving accurate segmentation of a canopy region was laid, which is of great significance for greenhouse cucumber phenotypic parameter measurements.

Keywords: greenhouse, cucumber canopy, machine vision, image segmentation, illumination, retinex

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1 Introduction

Growth parameters are important input information for modern, intelligent, and accurate control systems used in horticulture cultivation facilities. Currently, several nondestructive methods have been applied to the test of plant parameters, including machine vision[1], laser vision[2], remote sensing[3] and plant parameter reconstruction based on a morphological structure model[4]. These methods can perform nondestructive testing or refactoring of plant parameters for individual plants or large areas. Because plant parameters under identical growth conditions is different, individual plant parameters are not representative and cannot be used as a suitable basis for decision making in horticultural facility control systems. Additionally, large-scale remote sensing technology is not suitable for the environment of horticultural facilities. Thus, nondestructive online methods must be developed for plant parameters testing. Plant regions must be accurately segmented to perform phenotypic measurements. However, variability among natural lighting environment leads to low flora segmentation accuracy and stability, and to provide

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Biographies: Sun Guoxiang, PhD, research interests: machine vision and modeling biosystems, Email: sguoxiang@njau.edu.cn; **Li Yongbo,** PhD, Associate professor, research interests: modeling, biological systems and environment, Email: bewit@njau.edu.cn; **Hu Guyue,** MSc, research interests: Biological systems engineering, Email: 2014112034@njau.edu.cn; **Wang Xuan,** ME, research interests: Biological systems engineering, Email: 757899343@qq.com; **Zhang Yu,** PhD, research interests: Machine vision and modeling biosystems, Email: Zhangyu64@hotmail.com.

***Corresponding author: Wang Xiaochan,** PhD, Professor, research interests: modeling, biological systems and environment, Mailing address: Department of Electrical Engineering, College of Engineering, Nanjing Agricultural University, Box 96, 40 Dianjiangtai Road, Pukou, Nanjing. Tel:+86 25 58606567, Email: wangxiaochan@njau.edu.cn.

real-time accurate plant phenotypic information for facilities is difficult.

Currently, a number of scholars are studying on plant segmentation, primarily concentrating on measurements of fruit, leaf, canopy, and three-dimensional information. Due to the difference of plant biological properties, the color characteristics of the captured images vary according to the natural lighting conditions, which is another primary factor that affects accurate image segmentation because target recognition errors directly impact the subsequent image characteristic parameter calculations[5-6]. Thus, methods for reducing the influence of natural lighting effectively is a hot topic and a difficult issue when measuring plant phenotypic parameters using machine vision[7].

This research primarily focused on applying the segmentation algorithm under various lighting conditions for a cucumber canopy region in a natural horticulture facility environment. To extract the flora characteristic parameters, the flora canopy area should be accurately identified and extraneous background information should be removed. A number of studies have focused on flora segmentation algorithms, such as color vegetation indices, which was proposed to separate plants from soil and the background image residue, the index used was normalized difference vegetation index (NDVI)[8]. A similar index, the normalized green-red difference index (NGRDI), was used by Hunt et al.[9], and an improved vegetation index, the excess green minus excess red (ExG-ExR) index, was adopted by Meyer et al.[10-12] Prior research of Sun et al. primarily used the ExG-ExR segmentation algorithm to determine the canopy region, and the plant phenotypic parameters were back calculated by a statistical analysis of the canopy characteristic parameters[13,14]; however, the impact of natural lighting was not considered because it limited the segmentation algorithm. In a greenhouse, natural lighting makes a shadow of upper beam, which is projected onto the cucumber canopy and ground surface, this changes the color of foliage canopy images. Thus, the images must be pre-processed before being segmented. Jobson et al. proposed a center surrounding concept for single and multi-scale retinex algorithms to estimate the incident component of image, which was successfully applied to uneven illumination image compensation[15-18]. The retinex algorithm is commonly used for pre-processing images[19-21], and retinex theory is based on the color constancy of human vision[19]. Color constancy is a fundamental characteristic of visual nerve system. If lighting and reflection information can be separated in a given image by color constancy characteristic, the influence of external lighting on the image will be eliminated, which is the equivalent of considering only the object’s own reflection property; thus, the goal of image enhancement can be achieved[22].

The goal of this research was to provide guidance for real-time segmentation and phenotypic measurements of horticultural plant canopies in natural lighting environments. Based on current research, the color characteristics of cucumbers canopy under different lighting conditions were analyzed in this research. To enhance the canopy image of cucumbers, image enhancement was used to reduce the impact of lighting. Then, the modified excess green minus excess red (MExG-ExR) segmentation algorithm was used to segment the cucumber canopy. As a result, the accuracy and stability of cucumber canopy recognition was improved; in particular, excellent cucumber canopy recognition results were obtained under weak lighting, bright lighting and side lighting.

2 Materials and methods

2.1 Experimental design

The ‘Jinchun No.3’ cucumber variety was adopted and the experiments were conducted in a Venlo-type greenhouse located at Nanjing Agriculture University (118°46' N, 32°03' E), Nanjing, Jiangsu, China. The flora information detecting system consists of a webcam (3-megapixel, half-sphere, wide-angle, manufactured by Hikvision, Model: DS-2CD7254F-E, Hangzhou, China), a computer and flora information detecting software. The webcam was installed above the flora canopy. The focal length range of the lens was 2.7-9 mm, the viewing angle range was 101°-30.4°, the shutter speed was 1/25 s, the aperture was F1.6, and automatic white balance was not supported. The camera also was configured a RJ45

10 M/100 M adaptive Ethernet communication interface. The camera was installed on the top beam of greenhouse which is 3.75 m above the flora canopy, and the lens was angled straight downwards. To capture as many cucumbers as possible under the limited imaging distance and the suitable planting density, the focal length of the wide-angle camera was adjusted to 2.7 mm, the camera was focused manually to ensure that the image was clear, and the camera parameters keep unchanged during the test. The camera and monitoring computer were connected to the router in control room via a cable. Images were captured for 16 cucumber varieties using flora information detecting software. Canopy images of the greenhouse cucumbers were captured at times set from May 11, 2014 to June 29, 2014. The selected images were captured on May 27, 2014 at times of 10:17:12 (hh:mm:ss), 16:20:42 (hh:mm:ss), and 17:35:40 (hh:mm:ss), and a side lighting image, a bright lighting image, and a weak lighting image were included, respectively. These three images were used as the research objects in the following discussion.

The flow chart of greenhouse cucumber canopy image segmentation is shown in Figure 1. Firstly, multi-scale retinex image enhancement was performed on the original images captured under various lighting conditions. Then, the image enhancement performance was analyzed using five evaluation indexes of brightness, contrast, information entropy, average gradient, and average gray. Finally, the enhanced images were segmented by NDI, ExG, MExG, and MExG-ExR in the canopy region, and the indexes of the overlap ratio and recognition rate were used to assess the canopy segmentation performance.

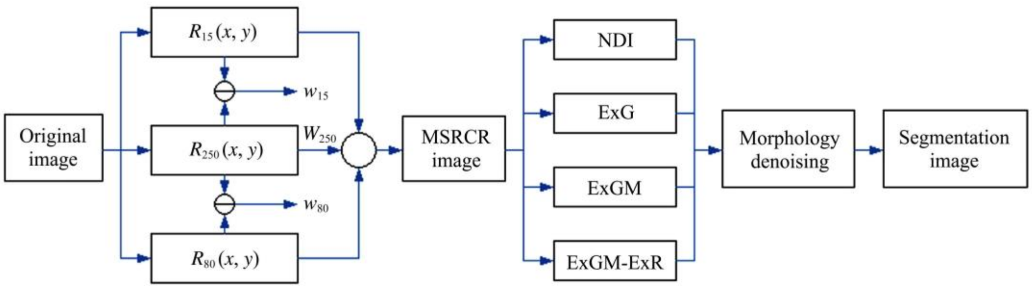


Figure 1 Flow chart of greenhouse cucumber canopy segmentation

2.2 Multi-scale retinex image enhancement algorithm

The basic concept of retinex theory is to separate the incident light L from the received image signal I and obtain the reflection property of the object R[22]. The image information of an object $I(x, y)$ perceived by the human eyes can be divided into two components: the incident light component $L(x, y)$ and the reflection light component $R(x, y)$, which are shown in Equations (1) and (2):

$$I(x, y) = L(x, y) \cdot R(x, y) \tag{1}$$

where, $I(x, y)$ is the brightness component perceived by human eyes or a sensor; $L(x, y)$ is the luminance component on the object from the surrounding environment; $R(x, y)$ is the reflection component from the target object and (x, y) are the image coordinates.

$$R(x, y)=\log\{[I(x, y)]/[I(x, y)*F(x, y)]\} \tag{2}$$

where, $R(x, y)$ is the image after brightness compensation; $F(x, y)$ is the environment function[21,22]; * represents a convolution operator and log is the natural log. $I(x, y)*F(x, y)$ estimates the incident component of the image by performing a convolution calculation of the brightness function and original image.

The multi-scale retinex algorithm is an image lighting compensation method that considers both the image dynamic region compression and image color constancy. For colored images, this algorithm can be described as follows:

$$R_{MSR,i}(x, y) = \sum_{n=1}^{N} w_n R_{n,i}(x, y) \tag{3}$$

where, $R_{MSR,i}$ is the MSR image of the i^{th} channel; N is the number of scales; i represents the i^{th} channel; n represents the n^{th} scale; $R_{n,i}(x, y)$ is the image lighting compensation result of the i^{th} channel in the n^{th} scale and w_n is the image lighting compensation weight in the n^{th} scale, which is usually taken as $w_n=1/N$.

Retinex with color restoration multiplies the reflection brightness obtained by multi-scale retinex, and a color recovery factor C_i was used to adjust the ratio of the colors in three channels, which are expressed in Equations (4) and (5):

$$R_{MSRCR,i}(x,y) = C_i R_{MSR,i}(x,y) \tag{4}$$

$$C_i = \log[\alpha \cdot I_i(x,y)] - \log[\sum_{i=1}^{3} I_i(x,y)] \tag{5}$$

where, C_i is the color recovery factor; $R_{MSRCR,i}$ is the MSRCR image of i^{th} channel and α is a constant coefficient (generally set between 0.5 and 2.0).

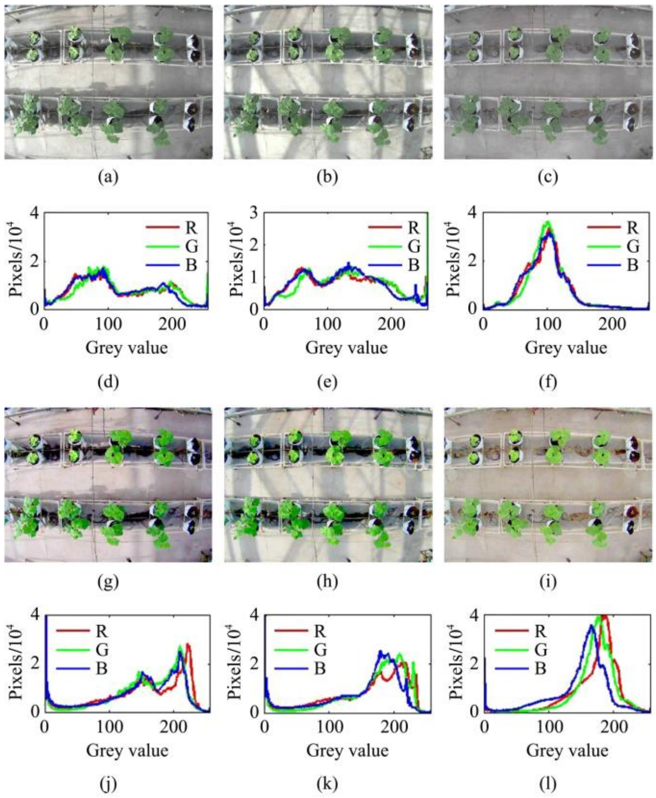
3 Results and discussion

3.1 Multi-scale retinex enhancement of cucumber canopy images

According to cucumber canopy segmentation flow, multi-scale retinex enhancement was first performed on the original images. Figures 2a, 2b and 2c show the original images of cucumber canopy, which include the side lighting image, bright lighting image and weak lighting image, respectively; Figures 2d, 2e and 2f are the RGB channel gray-scale histograms of Figures 2a, 2b and 2c, respectively; Figures 2g, 2h and 2i are the MSRCR images of Figures 2a, 2b and 2c, respectively; and Figures 2j, 2k and 2l are the RGB channel gray-scale histograms of Figures 2g, 2h and 2i, respectively. The color of cucumber canopy images were influenced by the natural lighting and the images reflect different colors. Particularly under the bright and side lighting conditions, the shadow of the greenhouse beam was projected on a portion of the canopy foliage, which resulted in differences of the canopy foliage color and the difficulty of canopy foliage segmentation increasing. Therefore, in this research, the canopy images were first pre-processed using the multi-scale retinex image enhancement algorithm, and based on this foundation, the images were segmented.

3.2 Performance of multi-scale retinex enhancement for cucumber canopy image

To evaluate the MSRCR image enhancement effect quantitatively, the five evaluation indexes of image brightness, contrast, information entropy, average gradient, and average gray were selected and used[21]. The statistical results are shown in Table 1.



Note: (a) Side lighting image; (b) Bright lighting image; (c) Weak lighting image; (d-f) RGB channel gray-scale histograms of (a-c); (g-i) MSRCR images of (a), (b), (c); (j-l) RGB channel gray-scale histograms of (g-i).

Figure 2 Greenhouse cucumber canopy images and gray-scale histograms

Table 1 Results of image enhancement performance

Evaluation index	Brightness	Contrast	Information entropy	Average gradient	Average value
	Original image				
Figure 2a	116.96	50.80	14.13	4.78	114.82
Figure 2b	127.17	50.26	14.65	5.07	124.43
Figure 2c	98.49	20.88	12.61	3.38	97.91
Mean	114.21	40.65	13.80	4.41	112.38
	MSRCR image				
Figure 2g	151.29	44.31	15.07	5.04	149.38
Figure 2h	158.02	42.35	15.35	5.02	153.53
Figure 2i	165.96	20.51	14.32	3.78	161.69
Mean	158.42	35.72	14.91	4.61	154.87

According to Table 1, the average value of brightness, information entropy, average gradient, and average value of the MSRCR images increased by 38.71%, 8.04%, 4.54%, and 37.81%, respectively, compared with those of the original images. These results indicate that with the increase of the brightness of MSRCR image, the amount of expressed information increase. Additionally, the edge of the objects in the images was clearer, and the image enhancement effect was achieved. Among the evaluation indexes, only the contrast decreased by 12.13%, and this decrease was primarily due to the relatively bright lighting in Figures 2a and 2b, and the strong contrast produced by the shadow area and no-shadow area. After MSRCR enhancement, the impact of the lighting was reduced, so the contrast was reduced. The above image evaluation index analysis showed that a good enhancement effect for the canopy images was achieved, which laid the foundation for achieving canopy segmentation under various lighting conditions.

3.3 Greenhouse cucumber canopy image segmentation

A number of detection studies have been done focusing on flora segmentation algorithms[23], including color vegetation indices, separating plants from the soil and image background residue, and these indexes include the NDI[8], NGRDI[9] and ExG-ExR[10-11]. In this study, the NDI, ExG, MExG, and MExG-ExR segmentations were selected. The formulas to calculate the NDI, ExG and ExR, are described by Equations (6-8). After applying the MSRCR treatment to the original images, the color of the cucumber canopy foliage changed and was no longer green. Thus, the ExG method was improved in this research, and the R, G and B coefficients in the ExG were adjusted, thus the modified excess green index (MExG) segmentation algorithm was formed as described by Equation (9):

$$\mathrm{NDI} = (G-R)/(G+R) \tag{6}$$

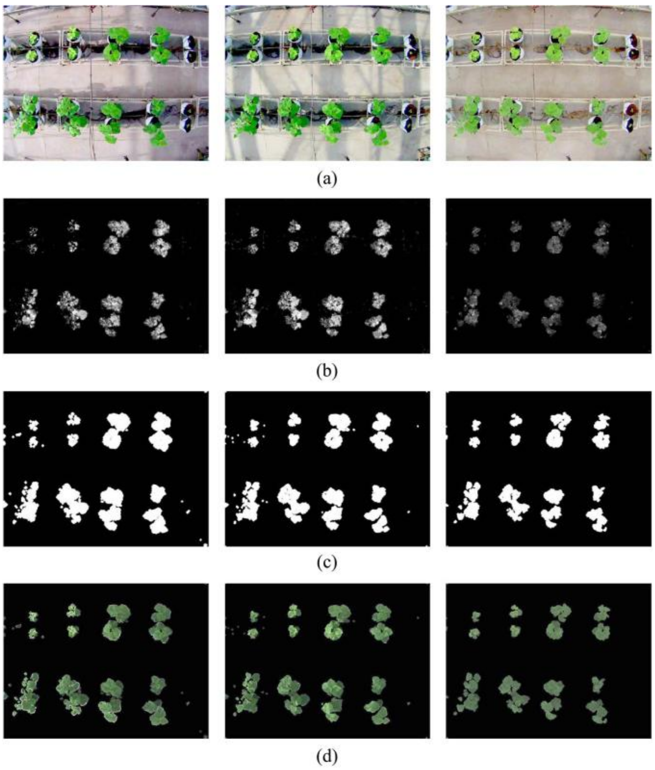
$$\mathrm{ExG} = 2G-R-B \tag{7}$$

$$\mathrm{ExR} = 1.4R-G \tag{8}$$

$$\mathrm{MExG} = 3G-0.5R-B \tag{9}$$

where, R is the red channel value of the image; G is the green channel value of the image; B is the blue channel value of the image; ExG is the excess green segmentation method; ExR is the excess red segmentation method; NDI is the normalized difference index and MExG is the modified excess green segmentation method.

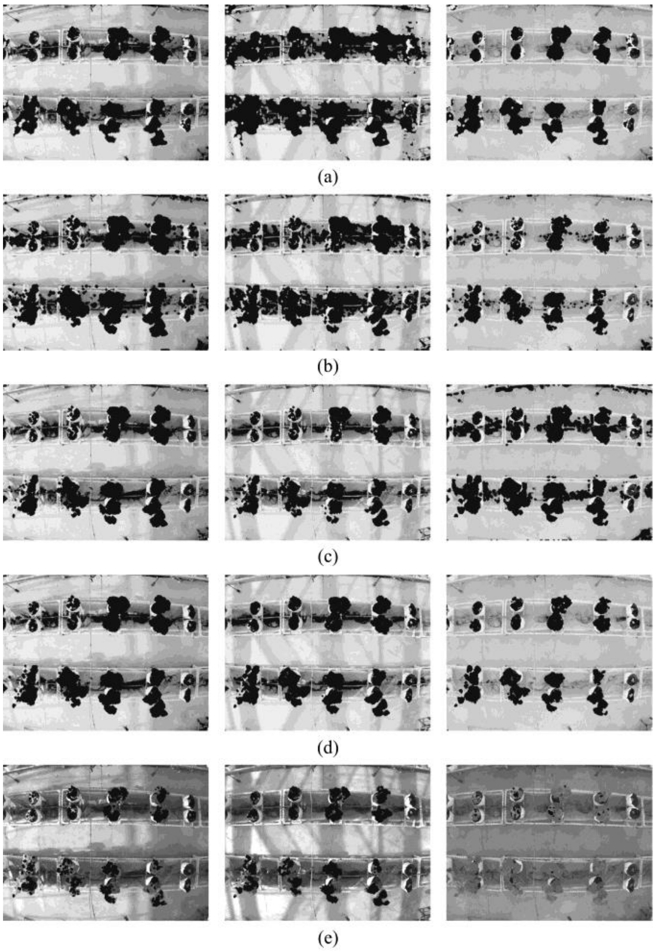
This research adopted four canopy segmentation algorithms including NDI, ExG, MExG and MExG-ExR to test the MSRCR image segmentation. Figure 3 shows the process diagram of canopy segmentation by MExG-ExR segmentation algorithm: Figure 3a shows the cucumber canopy MSRCR images and Figure 3b, which has been processed by Otsu's binarization[24], shows the MExG-ExR segmentation of the MSRCR images. Because numerous noise points occurred in the binary image, the figure was treated by the morphology processing method. Firstly, the images were treated with single noise etching, and the structuring element was a disk with a radius of 5 pixel. Then, the expansion treatment was performed on the canopy region three times with a radius of 2 pixel, and the noise reduction effect is shown in Figure 3c. An 'AND' operation was performed between Figure 3c and the original image, to obtain the cucumber canopy, the result is shown in Figure 3d, which indicates that the canopy segmentation is accurate and only a few missed-recognition and non-recognition regions occurs. The same segmentation process flow was used for the NDI, ExG, and MExG segmentation algorithms, and the results are shown in Figure 4. The final recognition regions of the segmentation algorithms are shown as black dots in the gray-scale MSRCR images.



Note: (a) Cucumber canopy MSRCR images under different lighting conditions; (b) MExG-ExR segmentation images of (a); (c) Noise reduction by the morphology processing method; (d) Segmentation effect of the cucumber canopy.

Figure 3 MSRCR image segmentation process

The images in Figures 4a and 4b show the segmentation results of NDI and ExG algorithms, respectively. A common shortfall of these two segmentation algorithms was the relative increase in missed-recognition regions. The image in Figure 4c shows the segmentation results of MExG, which produced a large amount of missed recognitions under the bright, side, and weak lighting conditions. The image in Figure 4d shows the segmentation results of MExG-ExR, which produced extremely few missed recognitions and misrecognition phenomena. A comparison of the segmentation results of the MSRCR and original images was performed using MExG-ExR segmentation algorithm on the original images. The segmentation results are shown in Figure 4e. When the segmentation was performed on the original images, the lighting impact produced inaccurate segmentation results, and a large amount of missed-recognition regions were created.



Note: (a) Segmentation results of MSRCR images using NDI algorithm; (b) Segmentation results of MSRCR images using ExG algorithm; (c) Segmentation results of MSRCR images using MExG algorithm; (d) Segmentation results of MSRCR images using MExG-ExR algorithm; (e) Segmentation results of original images using MExG-ExR algorithm.

Figure 4 Segmentation results of greenhouse cucumber canopy image

3.4 Performance of greenhouse cucumber canopy image segmentation algorithms

To evaluate the effectiveness of the plant canopy segmentation algorithms, two segmentation evaluation indexes, the overlap ratio and recognition rate, were established, as are shown in Equation (10) and (11). Three plant canopy images were selected from experimental period, and the rope tool in Photoshop was used to manually extract the plant canopy region for use as a reference[25]. Four segmentation algorithms, NDI, ExG, MExG and MExG-ExR were used to segment the greenhouse cucumber canopy region in the enhanced MSRCR images; additionally, the MExG-ExR segmentation algorithm was used to segment the original canopy images.

$$e=\frac{\sum_{i=m}^{j=n}F_{kq}(i,j)\cap F_{kp}(i,j)}{\sum_{i=m}^{j=n}F_{kp}(i,j)}\times 100\% \tag{10}$$

$$f=\frac{\sum_{i=m}^{j=n}F_{kq}(i,j)\cap F_{kp}(i,j)}{\sum_{i=m}^{j=n}F_{kq}(i,j)\cup F_{kp}(i,j)}\times 100\% \tag{11}$$

where, e is the overlap ratio; F_{kq} is the binary figure of the flora canopy segmentation image; k is the sequence number of the image; q is the serial number of the method; F_{kp} is the binary figure of the flora canopy region that was manually extracted using Photoshop; i is the row of the image; j is the column of the image; m is the number of image rows; n is the number of image columns and f is the recognition rate.

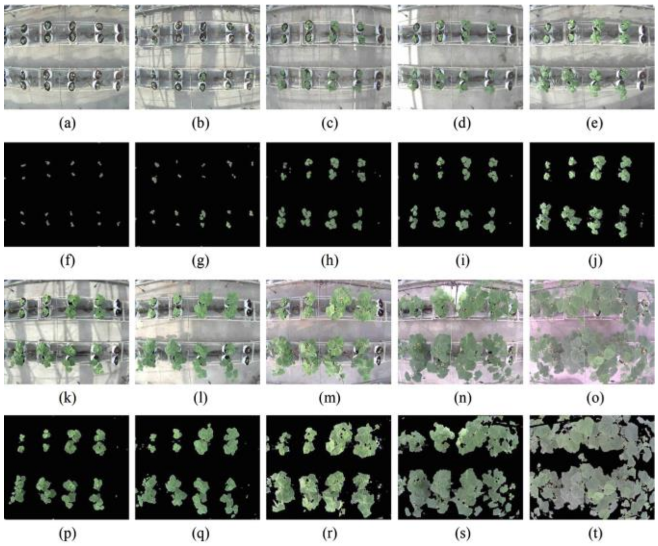
As is indicated in Table 2, the performance of NDI is impressive: the overlap ratio of the NDI was 82.27%-97.47%, and the recognition rate was 42.46%-77.43%. The recognition rate of NDI was slightly lower than its overlap ratio, thus indicating a small amount of leakage and a large amount of error in the partitioning of the flora canopy figures. The overlap ratio of ExG was 90.79%-97.85%, and the recognition rate was 50.08%-66.07%; thus, its segmentation performance was similar to that of NDI. The overlap ratio of MExG was 86.13%-99.81%, and the recognition rate was 44.73%-89.92%; and there were a greater number of missed-recognition regions under the weak lighting condition. The overlap ratio of MExG-ExR was greater than 98.85%, and the recognition rate was greater than 97.78%; the flora canopy was identified accurately, with very few mistakenly identified areas. Moreover, regardless of when the image was captured, the recognition performance of the flora canopy image was consistent. However, when the MExG-ExR segmentation algorithm was used on the original images, the overlap ratio was 3.74%-54.12% and the recognition rate was 3.74%-53.75%. The average values of the overlap ratio using NDI, ExG, MExG and MExG-ExR segmentation algorithms were 92.19%, 94.30%, 92.88%, and 99.27% respectively, and the coefficients of variation were 9.32%, 3.74%, 7.37% and 0.63%, respectively. When MExG-ExR was used on the original images, the average overlap ratio was 31.75% and the coefficient of variation was 83.31%. The average recognition rates using the NDI, ExG, MExG and MExG-ExR segmentation algorithms were 62.44%, 59.71%, 72.88%, and 98.31%, respectively, and the coefficients of variation were 28.85%, 14.20%, 33.70%, and 0.89%, respectively. When the MExG-ExR was used on the original images, the average recognition rate was 32.76% and the coefficient of variation was 79.22%. These results indicate that using MExG-ExR segmentation algorithm on MSRCR-treated images obtained the most stable performance.

Table 2 Performances of segmentation algorithms

Evaluation index	NDI (MSRCR)	ExG (MSRCR)	MExG (MSRCR)	MExG-ExR (MSRCR)	MExG-ExR (Original image)
	Overlap ratio/%				
Figure 2a	82.27	97.85	92.69	98.96	40.98
Figure 2b	97.47	94.27	86.13	98.85	54.12
Figure 2c	96.82	90.79	99.81	99.99	3.74
Mean	92.19	94.30	92.88	99.27	31.75
Coefficient of variance	9.32	3.74	7.37	0.63	83.31
	Recognition rate/%				
Figure 2a	67.43	62.98	89.92	97.83	40.80
Figure 2b	42.46	50.08	83.99	97.78	53.75
Figure 2c	77.43	66.07	44.73	99.32	3.74
Mean	62.44	59.71	72.88	98.31	32.76
Coefficient of variance	28.85	14.20	33.70	0.89	79.22

3.5 Applicability analysis of the segmentation algorithms

To verify the applicability of the segmentation algorithms, an adaptability test was performed from May 11 to June 29, 2014, and canopy images were captured during the test. A total of fifty images (an image each day) were selected, including fifteen images under bright lighting, fifteen images under side lighting, fifteen images under weak lighting and five images under uniform lighting. The multi-scale retinex enhancement was adopted as the image pre-processing method, and then, the NDI, ExG, MExG and MExG-ExR segmentation algorithms were used to segment the canopy area. The image segmentation results are shown in Figures 5a-5t, and the performance parameters of the four segmentation algorithms are shown in Table 3.



Note: (a-e) Original images collected in 2014-05-13, 2014-05-16, 2014-05-20, 2014-05-23 and 2014-05-26; (f-j) Segmentation results for (a-e); (k-o) Original images collected in 2014-05-27, 2014-05-30, 2014-06-04, 2014-06-09 and 2014-06-19; (p-t) Segmentation results for (k-o).

Figure 5 Segmentation results of applicability test

Table 3 Performances of the segmentation algorithms

Evaluation index	NDI (MSRCR)	ExG (MSRCR)	MExG (MSRCR)	MExG-ExR (MSRCR)	MExG-ExR (Original image)
	Overlap ratio/%				
MIN	81.50	90.50	86.13	98.05	3.61
MAX	97.47	99.80	99.81	100.00	66.00
Mean	92.37	95.97	96.89	99.28	38.39
	Recognition rate/%				
MIN	42.46	46.72	44.73	97.70	3.25
MAX	78.50	66.80	93.80	99.70	65.50
Mean	72.65	61.83	89.35	98.91	37.95

Table 3 shows the results of segmentation algorithms NDI, ExG, MExG and MExG-ExR, which were used to segment the canopy area of the images after the MSRCR enhancement pre-processing.

The statistics in Table 3 showed that when the images were segmented by MSRCR enhancement pre-processing, the overlap ratio average values of NDI, ExG, MExG and MExG-ExR were 92.37%, 95.97%, 96.89% and 99.28%, respectively, and the recognition rate average values were 72.65%, 61.83%, 89.35% and 98.91%, respectively. The MExG-ExR segmentation method got a high accuracy and stability, and the NDI, ExG and MExG segmentation methods created serious leakage areas and false recognition areas. When MExG-ExR was used to segment the original images, the average overlap ratio was 38.39%, and the average recognition rate was 37.95%, the canopy images were influenced by natural light and leakage recognition and false recognition were more serious. The results showed that the natural light interference in the canopy images could be reduced when the images were enhanced by the MSRCR process and the MExG-ExR segmentation method obtained the best segmentation performance. Thus, the MSRCR images segmented by MExG-ExR could provide the foundation for greenhouse cucumber canopy information detection.

4 Conclusions

In this research, a segmentation algorithm for cucumber canopy image regions under different lighting conditions in a Venlo-type glass greenhouse environment was established using image processing techniques. The primary conclusions are as follows:

(1) Multi-scale retinex image enhancement theory was used to enhance cucumber canopy images taken under different lighting conditions to reduce the interference of these lighting conditions. The image enhancement performance was assessed by five image indexes: brightness, contrast, information entropy, average gradient, and average value. The results showed that compared with the original images, the average brightness, information entropy, average gradient, and average gray values of the MSRCR images increased by 38.71%, 8.04%, 4.54%, and 37.81%, respectively, whereas the contrast decreased by 12.13%. These results indicated that the canopy images were effectively enhanced, thus providing a foundation for achieving canopy segmentation under different lighting conditions.

(2) The NDI, ExG, MExG and MExG-ExR segmentation algorithms were used to segment the canopy region of the MSRCR images, and two evaluation indexes, overlap ratio and recognition rate were established to evaluate the segmentation performance. The results indicated that the average segmentation overlap ratio with NDI, ExG, MExG and MExG-ExR segmentation algorithms applied to images in the test (fifty images) were 92.37%, 95.97%, 96.89% and 99.28%, respectively, and when the MExG-ExR segmentation algorithm was used on the original images, the average overlap ratio was 38.39%. The average recognition rates using NDVI, ExG, MExG and MExG-ExR algorithms were 72.65%, 61.83%, 89.35%, and 98.91%, respectively, and the average recognition rate was 37.95% when MExG-ExR was used on the original images. These results indicate that using the MExG-ExR segmentation algorithm on the MSRCR-treated images obtained the most stable performance.

Using multi-scale image enhancement theory combined with MExG-ExR segmentation algorithm, accurate segmentation of greenhouse cucumber canopy regions under different lighting conditions was achieved, and such segmentation provides a foundation for greenhouse cucumber phenotypic parameter measurements. The other papers in the earlier stages of this research have discussed the construction of the back-calculation algorithm for greenhouse cucumber phenotypic parameters from canopy image parameters[13,14], which was not described in details in this paper. Subsequent research will focus on solving the issue of obtaining rotational invariance characteristic parameters as a method of promoting this technique, which can achieve online nondestructive testing of plant groups and provide a real-time decision-making basis for control systems. In addition, this technique has the advantages of low cost and easy of realization and promotion and therefore owns good application potential.

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