Evaluation of grapevine sucker segmentation algorithms for precision targeted spray

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Abstract: Chemical sucker control has been proven to be an effective substitute for manual and mechanical removals. Recognition and location of suckers is the key technology of precision targeted spray which can reduce spray volume than current spray pattern. The goal of this research was to develop a quick and effective segmentation algorithm of sucker images for real-time mobile targeted spray by evaluating and comparing seven segmentation algorithms categorized into segmentation based on color feature (ExG, ExGExR, and CIVE), *K*-means clustering segmentation in CIE $L^*a^*b^*$ space (K-Lab), and mean shift clustering segmentation based on color feature (ExG-MS, ExGExR-MS, and CIVE-MS) from time consuming and accuracy. The results indicated that ExGExR and CIVE took shorter time than other algorithms, and were more suitable for real-time operation. By further evaluating segmentation accuracy, ExGExR, CIVE, and mean shift algorithms were acceptable to kill suckers. And ExGExR was the best algorithm for sucker segmentation in consideration of time consuming and accuracy, next came CIVE.

Keywords: grapevine suckers; image segmentation; color feature; *K*-means; mean shift
DOI: 10.3965/j.ijabe.20150804.1527

Citation: Xu S S, Li W B, Kang F, Zheng Y J, Lan Y B. Evaluation of grapevine sucker segmentation algorithms for precision targeted spray. Int J Agric & Biol Eng, 2015; 8(4): 77－85.

1 Introduction

Suckers are nonbearing shoots, canes, or limbs that emanate from the rootstock area of grapevine trunk[1]. Suckers growing on a grapevine may lead to over-cropping, which increases the possibility of attack from pathogens and alters the fruit/shoot ratio. Therefore, suckers must be removed to maintain the energy of the vines above ground and prevent their interference with cultural practices in vineyards. Besides, suckers must be removed several times during a season because of its repeated growing.

Sucker control treatments include manual removal, mechanical removal and chemical control of sucker's growth. Manual removal is cutting suckers off by using sharp knife-like tools. Although this operation can completely removes suckers and leaves little damage on grapevines, it is time consuming and requires much labor force that is costly. The mechanization of this operation is more efficient than manual removal, but it is harmful to young plants, which can be damaged by rotating tools. In addition, mechanical removal is not so comprehensive that often leaving stubs from which buds would arise and grow to new sucker later [2].

Received date: 2014-10-28 **Accepted date:** 2015-08-07
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Many researches focused on chemical control of sucker growth have been conducted in past decades in order to seek more effective alternatives for sucker removal. 1-Naphthaleneacetic acid (NAA)[3] and Paclobutrazol[4] have been proven effectively to control growth of trunk and crown sucker as a potential inhibitor for grapevines. These attempts made chemical control an effective alternative and gradually replaced manual and mechanical removal.

At present, the spray pattern of chemical control is non-selective band spray which keeps spraying chemical directly to the rootstock area of grapevines with the moving of vehicle. Chemical is over applied because suckers do not appear on all vines and vary in quantity and size, and the chemical is also applied to the inter-vine non-suckering area. Targeted spray with different chemical volume based on specific situation of suckers on a grapevine can observably reduce environmental pollution. Accurate sucker recognition is the primary key technology for this precision targeted spray.

Current crop recognition methods include spectral and image analysis. Spectral analysis[5] is a method that people obtain crop reflected spectrum by sensors to recognize weeds, pests and diseases according to the rich spatial and spectral characteristics of crops. However, the spectral data are often limited to uncertain factors, such as ambient light, solar elevation angle, and the time of spectral image acquisition[6] etc, leading to results that may not truly reflect the actual information. Recognition by image processing is to analyze crop images by crop characteristics including color, texture, shape and location[7-9], etc. Environmental conditions and instruments have less influence on them, which make it widely used in identification of crops in agriculture and forestry.

Recognition of grapevine suckers for precision targeted spray is reported rarely so far[10]. Under this premise, the goal of this research was to figure out proper segmentation algorithms for sucker images to feed sucker information for precision targeted spray. Total seven segmentation algorithms were evaluated from both time consuming and accuracy. Each algorithm will be detailed described in the following section.

2 Sucker image segmentation algorithms

2.1 Segmentation algorithms based on color feature

Segmentation algorithms based on color feature are widely used in crop recognition due to the fact that crops are often rich in color information[11,12]. According to the observation results in field, suckers show “green” in early stage and “reddish green” in later growth stage. Figure 1 shows the distribution of R, G, and B value of the pixels in a sucker image taken in vineyard (Figure 1a). The distributions of R, G, and B value at the top (L_1; Figure 1b), middle (L_2; Figure 1c), and low (L_3; Figure 1d) position of the suckers were analyzed with Matlab software. The color features (R, G, and B) at all positions (L_1, L_2, and L_3) indicated the same distribution tendency as shown in Equation (1). G value in sucker area was obviously higher than R value, and R value was higher than B value. In contrast, the values in background area did not follow the relationship. According to the analysis, suckers should be segmented from the background based on color features.

$$G_{value} > R_{value} > B_{value} \tag{1}$$

where, G_{value}, R_{value}, and B_{value} are the G, R, and B values of the pixels in the sucker image, respectively.

In this research, three segmentation algorithms based on color features were chosen for sucker recognition including Extra-green algorithm (ExG), Extra-green and Extra-red algorithm (ExGExR) and Color Index of Vegetation Extraction algorithm (CIVE). ExG[13] increases the weight of G value intentionally to enhance the contrast ratio of green objects to a non-green background. Equation (2) was used in ExG to gray scale sucker image:

$$I_{ExG} = \begin{cases} 0, & 2G-R-B \leq 0 \\ 255, & 2G-R-B \geq 255 \\ 2G-R-B, & others \end{cases} \tag{2}$$

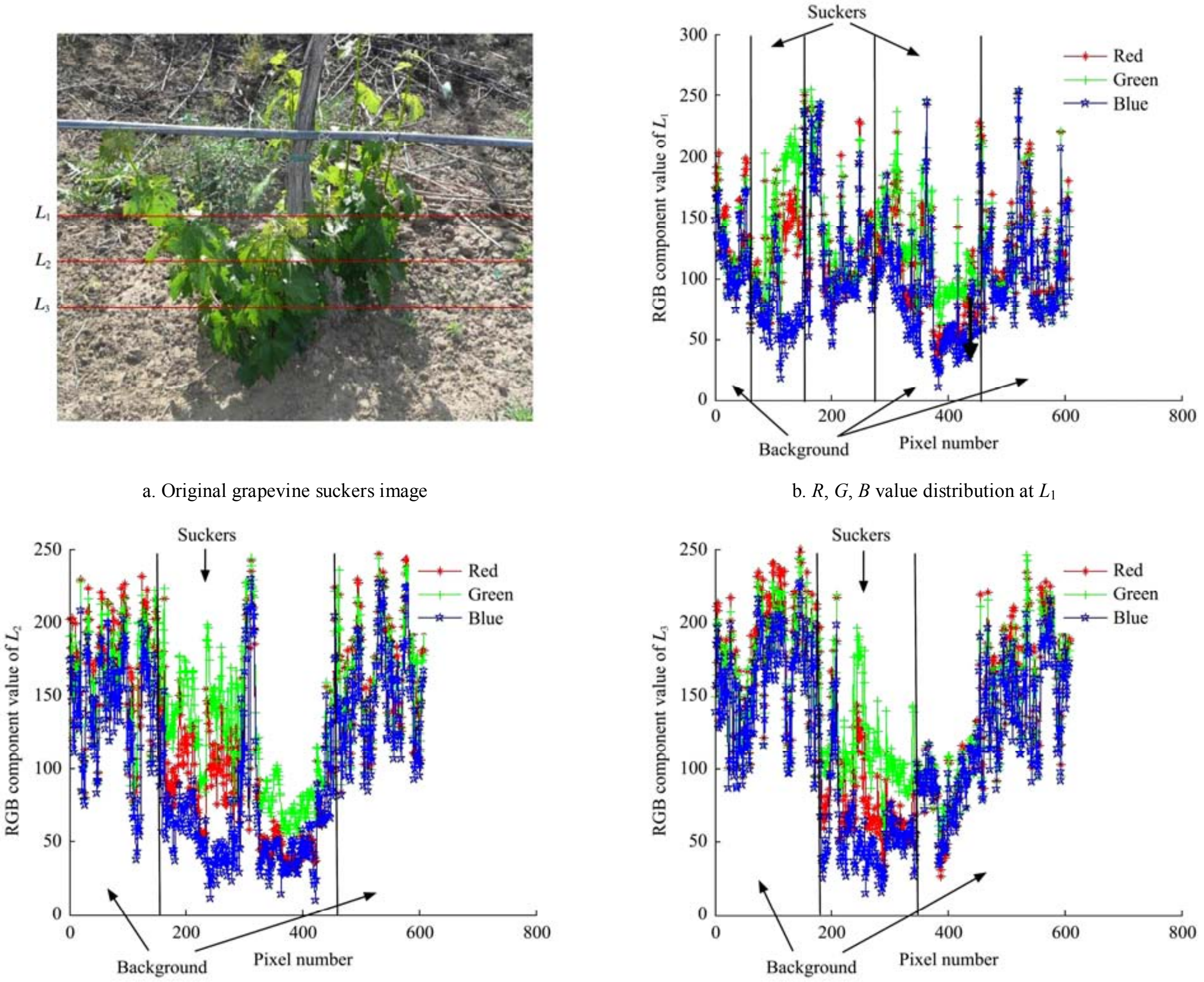
where, I_{ExG} is the ExG gray value of each pixel in sucker image. According to the observation in field, suckers have a color fact that green is the dominant color with slight red interspersed[14]. Thereby, ExGExR[15]

(Equation (3)) and CIVE[16] (Equation (4)) were chosen as follows:

$$I_{ExGExR} = \begin{cases} 0, & \text{if } value \le 0 \\ 255, & \text{if } value \ge 255 \\ 3G - 2.4R - B, & others \end{cases} \tag{3}$$

$$I_{CIVE} = \begin{cases} 0, & \text{if } value \le 0 \\ 255, & \text{if } value \ge 255 \\ 0.441R - 0.881G + 0.385B + 18.787, & others \end{cases} \tag{4}$$

where, I_{ExGExR} and I_{CIVE} are the ExGExR and CIVE gray values of each pixel in sucker image, respectively.



a. Original grapevine suckers image

b. R, G, B value distribution at L_1

c. R, G, B value distribution at L_2

d. R, G, B value distribution at L_3

Figure 1 Distributions of R, G, and B value at the top (L_1), middle (L_2), and low (L_3) position of suckers

2.2 *K*-means clustering segmentation in CIE L*a*b* space

Suckers can only breed from the rootstock area of the vine trunk. It is noted that sucker images taken in vineyards usually have a complicated background, which can be attributed to the existence of the trunk, pipeline, weeds and adjacent vine rows. The situation can be improved by using a baffle plate placed right behind the suckers, but not practical in actual operation[10]. Plus uneven illumination caused by the occlusion of the tree crown, it is very important to select a suitable color space for sucker segmentation.

CIE L*a*b* color space is a color-component space with one dimension of L* for lightness (ranging from 0 to 100; 0 yields black and 100 indicates diffuse white) and a* (ranging from −128 to +127; negative value indicates green while magenta for positive value) and b* (ranging from −128 to +127; negative value indicates blue and yellow for positive value) as the color components for other two dimensions. Bai et al.[17] segmented rice seedlings by using morphology modeling in CIE L*a*b* color space with an accuracy of 87.2%. Li et al.[18] identified citrus red mite with *K*-means clustering method in CIE L*a*b* color space, and compared the accuracy of different number of clustering center.

Li et al.[19] segmented color images of grape diseases by using the K-means clustering algorithm in CIE $L^*a^*b^*$ color space and morphology, which could satisfactorily segment the diseased regions from the images. Therefore, a K-means clustering algorithm in CIE $L^*a^*b^*$ color space (K-Lab) was established aiming to rapidly recognize grapevine suckers.

Firstly, an original sucker image needs to be converted from the RGB color space (RGB) to the CIE $L^*a^*b^*$ space ($L^*a^*b^*$). Since it cannot be converted from RGB to $L^*a^*b^*$ directly, it was firstly converted from RGB to XYZ color space (Equation (5)), then to $L^*a^*b^*$ using Equation (6) to (8).

$$\begin{bmatrix} X \\ Y \\ Z \end{bmatrix} = \begin{bmatrix} 2.7689 & 1.7518 & 1.1302 \\ 1.0000 & 405907 & 0.0601 \\ 0.0000 & 0.0565 & 5.5943 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix} \tag{5}$$

$$L^* = \begin{cases} 116 f(\frac{Y}{Y_0})^{1/3} - 16, & \frac{Y}{Y_0} > 0.008856 \\ 903.3 f(\frac{Y}{Y_0})^{1/3}, & \frac{Y}{Y_0} \le 0.008856 \end{cases} \tag{6}$$

$$a^* = 500[f(\frac{X}{X_0}) - f(\frac{Y}{Y_0})] \tag{7}$$

$$b^* = 200[f(\frac{Y}{Y_0}) - f(\frac{Z}{Z_0})] \tag{8}$$

where, X_0, Y_0, and Z_0 are the tristimulus values of CIE standard illuminant. The light source D50 (0.9642, 1.0000, 0.8249) was used in this research. Secondly, because all of the color information is in a^* and b^* layers, a^*b^* space of the sucker image was extracted from the CIE $L^*a^*b^*$ color space, after which the objects were converted into pixels only with a^* and b^* value. Thirdly, K initial cluster centers were randomly selected from a^*b^* space which contained $M \times N \times 2$ pixels. M and N are the row and column of the image, respectively. Fourthly, other remaining objects were assigned to the corresponding cluster region by finding the minimum Euclidean distance between them and the K initial cluster centers and marked. The mean value of all objects assigned to each cluster region was obtained, and K new cluster centers were established based on the mean value[20]. Repeat the process mentioned was. K invariable cluster centers were eventually found out and were treated as the segmentation results.

In this research, sucker segmentation performed best at $K = 2$, according to many experiments. Meanwhile, it was noted that the iterations did not influence the performance of the segmentation. Here, once iteration was used in order to achieve fast segmentation.

2.3 Mean shift clustering segmentation based on color feature

The mean shift is a probability density gradient estimation method, which can accurately segment crops from image. Zheng et al.[21] extracted five features including hue, saturation, R, G and B, based on which a mean shift clustering segmentation was developed to segment green plants from images and then a combination of mean shift with Fisher discrimination for segmenting green crops was proposed. This method had a high accuracy but was time-consuming because of the excessive clustering features. It is not suitable for real-time targeted sucker chemical control. Si et al.[22] selected a color difference $R - B$ as the color feature, gray average, standard deviation and entropy as the texture feature forming a feature vector space to segment green apples using K-means clustering method. It had poor recognition accuracy on the fruits with low brightness.

Three algorithms of mean shift clustering segmentation based on color feature were proposed in this research for sucker segmentation, including mean shift clustering segmentation based on ExG (ExG-MS), ExGExR (ExGExR-MS) and CIVE (CIVE-MS). ExG, ExGExR and CIVE are exactly the ones described in section 2.1. The three mean shift clustering segmentation algorithms based on color feature followed the same strategy, as shown in Figure 2.

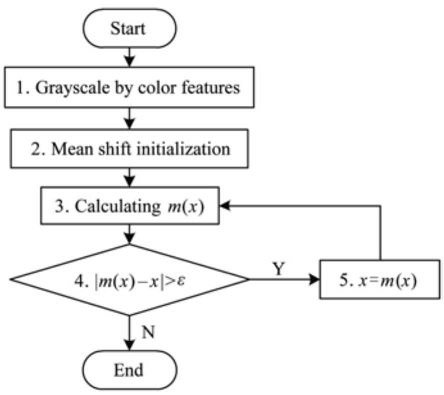


Figure 2 Flowchart of the three mean shift clustering segmentation algorithms based on color feature (ExG-MS, ExGExR-MS and CIVE-MS)

Three color features (ExG, ExGExR, and CIVE) were firstly extracted using Equations (2)-(4) in RGB, respectively, and then grayed the original sucker image into grayscale image (step 1 in Figure 2). The initial spatial domain bandwidth (s) and range bandwidth (r) if satisfying Equation (10) (step 4 in Figure 2) and were both set to 3 by experiment (step 2 in Figure 2). Then, the coordinates of the cluster centers m(x) were calculated using Equation (9) in "Calculating $m(x)$" (step 3 in Figure 2). $m(x)$ will be assigned to x returned back to step 3 to recalculate $m(x)$ until it failed to satisfy Equation (10). Here, ε was set to 0.001; iteration would be terminated by then.

$$m(x)=\frac{\sum_{i=1}^{n}K_{s,r}(x)w(i)x_i}{\sum_{i=1}^{n}K_{s,r}(x)w(i)} \tag{9}$$

$$m(x)-x|>\varepsilon, \qquad \varepsilon=0.001 \tag{10}$$

where, x is the pixel value of current clusteredpoint; x_i is the pixel value of the i^{th} point in a square centered by x with $2s$ in side length. $w(i)$ is the weight for xi and set to 1. $K_{s,r}$ is the probability density function[23] as defined in Equation (11):

$$K_{s,r}(x)=\frac{1}{s^2r^2}\exp(-\frac{\|x_i-x\|^2}{2s^2})\exp(-\frac{\|x_i-x\|^2}{2r^2}) \tag{11}$$

2.4 Experimental method

According to the description in section 2, there were totally seven algorithms for sucker segmentation evaluated by experiment including ExG, ExGExR, CIVE, K-Lab, ExG-MS, ExGExR-MS, and CIVE-MS. All sucker images were acquired at a commercial vineyard located near Prosser, WA, USA using a color CCD camera (GC1920C, Prosilica, Inc., Burnaby, British Columbia, Canada) in May 2010 on a sunny, cloudless day. The camera was set to capture images at 1 280×960 pixel spatial resolution with the maximum frame rate of 32 fps. The grape cultivar was Reisling wine grape. It has been proven that chemical spray cannot kill suckers with pixel size more than 150 000 in feasibility research. Thereby, in this research, eight different sizes of suckers whose pixel size less than 150 000 were chosen for the experiment (Table 1), which represented different size situations of suckers that can be removed by chemical spray. Eight images were taken for each size. The original sucker images with a pixel size of 608×425 used for algorithm evaluation were intercepted from the images taken in the vineyard for lowering the algorithms time consuming.

Table 1 Sucker sizes selected for evaluation experiment

Size No.	S_1	S_2	S_3	S_4	S_5	S_6	S_7	S_8
Pixel Size	134,524	130,790	104,508	758,68	44,550	17,820	5,436	2,867

3 Results and discussion

3.1 Evaluation of time consuming

All algorithms ran in Matlab R2010a on the same laptop (Lenovo, Think Centre 1 Mini Tower with 2.20 GHz 2 processors, 3.0 GB RAM, and 32-bit operating system). Other software was disabled during running. The time consumed for processing the same original sucker image using the same algorithm varied slightly so that five repetitions were conducted for each image under each algorithm and the time consumed of five repetitions was averaged and treated as the final consumed time for the image under certain algorithm. The time consumed of algorithms is listed in Table 2.

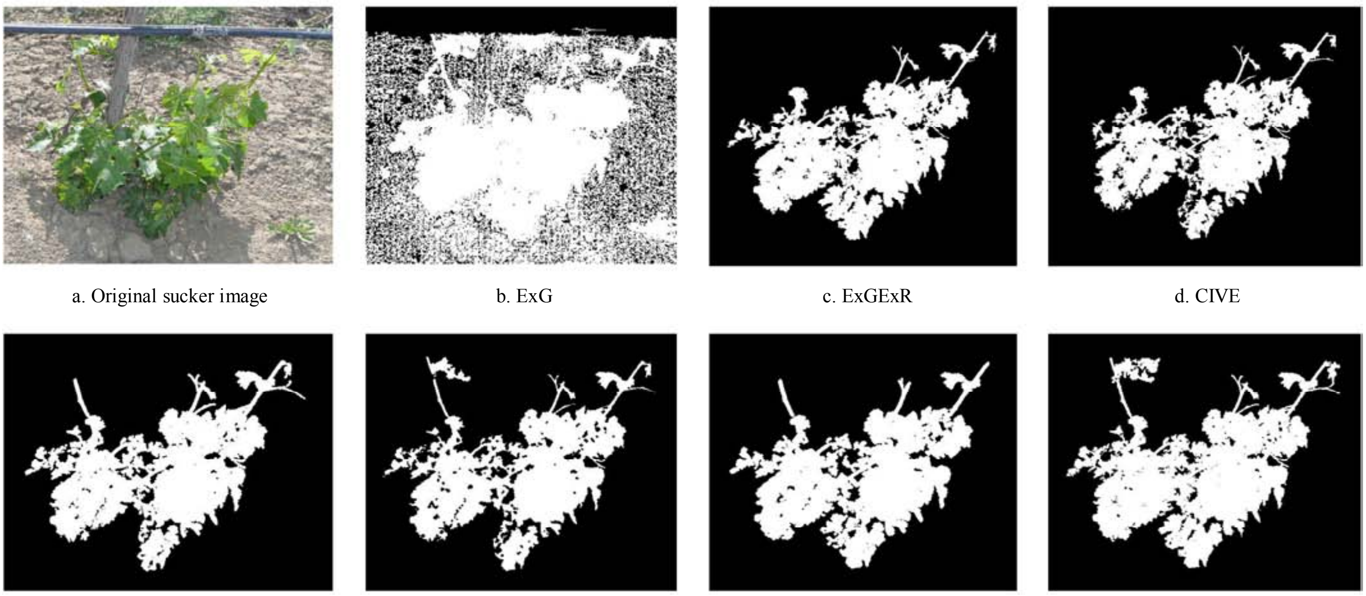
Table 2 Time consumptions of seven segmentation algorithms on all sucker sizes.

Algorithms	Time consumed (s)									
	S_1	S_2	S_3	S_4	S_5	S_6	S_7	S_8	Overall average	Standard deviation
ExG	1.241	1.146	2.576	3.568	2.689	2.658	4.398	3.663	2.742	1.067
ExGExR	0.827	0.674	0.658	0.853	0.453	0.876	0.578	0.247	0.646	0.203
CIVE	0.725	0.662	0.868	0.477	0.186	0.868	0.477	0.186	0.556	0.255
K-Lab	2.252	2.147	2.276	2.481	2.845	2.782	3.010	2.328	2.515	0.301
ExG-MS	9.983	10.032	10.457	9.688	9.818	10.135	9.734	9.818	9.958	0.238
ExGExR-MS	10.760	10.372	10.027	9.525	9.576	10.027	9.525	9.576	9.924	0.430
CIVE-MS	12.492	12.182	13.056	13.179	13.859	13.178	13.154	16.985	13.511	1.394

The results of time consumption showed that ExGExR and CIVE took shorter time with the overall average of 0.646 s for ExGExR and 0.556 s for CIVE, respectively. ExG had large time consuming variation with a standard deviation of 1.067 s which was influenced by sucker size. K-Lab had an overall average of 2.515 s. Mean shift algorithms took more than 9 s. However, sucker segmentation is only a part of its recognition and location. The whole process also involves sucker image acquisition, noise exclusion, sucker size determination and location in actual operation which will take more time. Currently the acceptable travel speed for precision targeted spray is about 3.2 km/h[14]. The travel distance will reach more than 1 m if the consumed time by sucker recognition and location is more than 1 s, which may miss the best spray time or even the suckers. Based upon this real-time requirement, it can be concluded that ExGExR and CIVE were suitable for precision targeted spray on the aspect of time consuming.

3.2 Accuracy of sucker segmentation

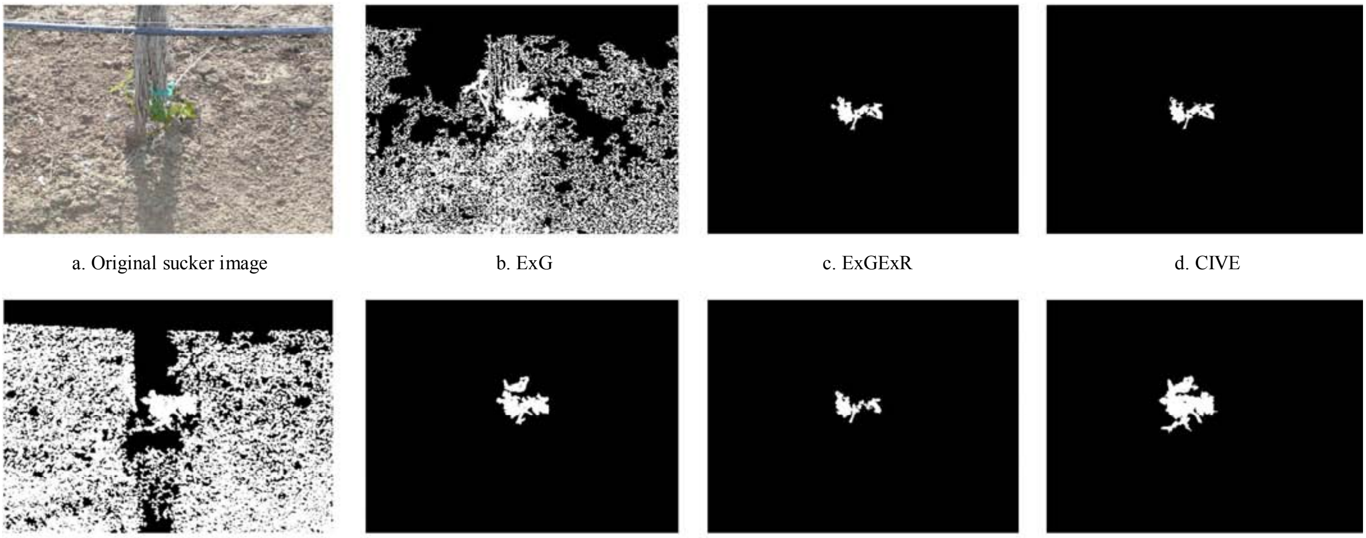
The accuracies of all seven algorithms were evaluated and compared in this section. The binary segmentation results of all algorithms were illustrated in Figure 3 and 4 for better understanding their performance. Due to space limit, only the results of two sizes suckers were listed (Figure 3 for S_1 and Figure 4 for S_7). The results of other sizes were similar to them. The segmentation results showed that all other algorithms except ExG and K-Lab can effectively segment suckers of all sizes. ExG failed to do it because of not taking in account of the red component of sucker color and over-extracting greenness from the background (Figure 3b; Figure 4b). K-Lab failed to correctly segment suckers with small sizes (S_5 to S_8) (Figure 4e) because bad clustering occurred and led to over-extracting greenness from the background. Both ExG and K-Lab needed further process including dilation and erosion to filter weeds due to its poor effectiveness (Figure 3b; Figure4b and 4e). Unfortunately, small size suckers will be omitted during erosion. Therefore, the seven algorithms were followed by a further process that searching the maximum connected region for weeds exclusion and edge correction in order to achieve better binary segmentation. The maximum connected region was treated as the suckers. Finally, a color segmentation of suckers was completed by displaying the segmented suckers using the color in the corresponding region of the original sucker image. The color segmentation results of all seven algorithms followed by the above further process on size S_1 are shown in Figure 5.



a. Original sucker image b. ExG c. ExGExR d. CIVE

e. K-Lab f. ExG-MS g. ExGExR-MS h. CIVE-MS

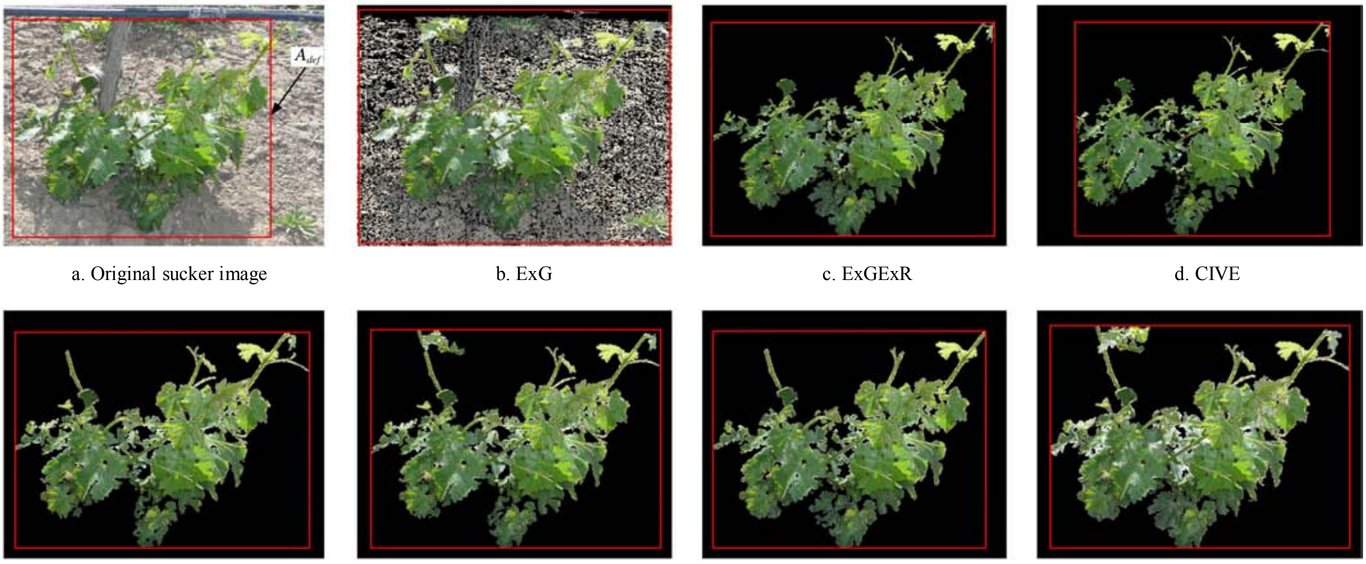
Figure 3 Sucker segmentation results of seven algorithms on size S_1



a. Original sucker image　　b. ExG　　c. ExGExR　　d. CIVE

e. K-Lab　　f. ExG-MS　　g. ExGExR-MS　　h. CIVE-MS

Figure 4　Sucker segmentation results of seven algorithms on size S_9



a. Original sucker image　　b. ExG　　c. ExGExR　　d. CIVE

e. K-Lab　　f. ExG-MS　　g. ExGExR-MS　　h. CIVE-MS

Figure 5　Sucker color segmentation results of seven algorithms on S1.

Red rectangles in (b)-(h) are the corresponding sucker rectangles of the seven algorithms after color segmentation

Actually the chemical spray volume and width are determined by the circumscribed rectangle of suckers in mobile targeted spray in vineyards. Here, it was called sucker rectangle. So an area-based criterion was established for evaluating the sucker segmentation accuracy as defined in Equation (12):

$$A_{TrueR}=\begin{cases}\left|1-\dfrac{|A_{seg}-A_{def}|}{A_{def}}\right|\times 100\%, & \dfrac{|A_{seg}-A_{def}|}{A_{def}}\leq 1\\ 0, & \dfrac{|A_{seg}-A_{def}|}{A_{def}}>1\end{cases}\qquad(12)$$

where, A_{TureR} is the segmentation accuracy; A_{seg} (pixel) is the sucker rectangle area circumscribing the suckers after the color segmentation (Figure 5); A_{def} (pixel) is the actual area of sucker rectangle in the original sucker image (manually measured by Photoshop; Figure 5a). The segmentation accuracies of all seven algorithms are listed in Table 3.

ExG treated almost the entire region of the image as the sucker rectangle (Figure 5b) on all sizes, which was defined as that the segmentation accuracy was zero (Equation (12)). It was because that ExG did not take in account of the red component of suckers and over-extracted greenness from the background. The accuracy of ExGExR and CIVE on all size performed a good segmentation. ExGExR had an average of 90.3%

and standard deviation of 6.4% while CIVE had an average of 83.7% and an 8.3% standard deviation. Bai et al.[17] segmented crop with accuracy rate of 63.2% and 74.2% by using ExGExR and CIVE algorithm respectively. Zhang[24] segmented corn, soybean etc. with accuracy rate of 87.41% and 87.03% by using ExGExR and CIVE algorithm respectively. Both of the segmentation accuracy rates by using ExGExR algorithm were lower than the segmentation of suckers in this research. However, the accuracy of CIVE algorithm developed by Zhang et al. was higher than our segmentation results due to the low accuracy when dealing with small size suckers. K-Lab performed good segmentation on S_1 (96.9%) (Figure 5e) to S_4 (95.7%). However, similarly to ExG, almost the entire region of the image was considered as the sucker rectangle by K-Lab on small size suckers (S_5 to S_8) due to the bad clustering, as shown in Figure 5e, which was also defined as zero accuracy. Mean shift algorithms (ExG-MS, ExGExR-MS, and CIVE-MS) achieved more accurate segmentation on all sizes. Both algorithms based on the color feature of G and R (ExGExR and ExGExR-MS) performed best segmentation accuracy in their respective category.

Table 3 Segmentation accuracies of seven segmentation algorithms on all sucker sizes.

Algorithm	Segmentation accuracy									
	S_1	S_2	S_3	S_4	S_5	S_6	S_7	S_8	Average	Standard deviation
ExG	0	0	0	0	0	0	0	0	0	–
ExGExR	98. 9%	94. 0%	93.6%	92.9%	88.9%	87.0%	91.5%	75.8%	90.3%	6. 4%
CIVE	94. 8%	84. 0%	86.3%	87.8%	86.9%	80.5%	85.0%	64.2%	83.7%	8.3%
K-Lab	96.9%	97.5%	96.8%	95.7%	0	0	0	0	0	–
ExG-MS	99.9%	99.6%	99.3%	89.8%	88.3%	80.3%	74.4%	86.8%	89.8%	8.6%
ExGExR-MS	99.9%	90.4%	95.8%	93.5%	86.2%	89.6%	97.8%	76.7%	91.2%	6.9%
CIVE-MS	99.6%	99.9%	98.5%	93.4%	90.7%	79.4%	91.9%	65.4%	89.9%	11.1%

Although the accuracies of seven algorithms except ExG and K-Lab ranged from 83.7% to 91.2% because several twigs or leaves at the branch end of suckers were missed, the main body of suckers closed to its rootstock was clearly identified. It is acceptable because suckers can be removed as long as its main body is recognized and treated with chemical in precision targeted spray. The presence of weeds and the posture of suckers were the factors that lowering the segmentation accuracy. Future work is being conducted on two aspects: one is to develop algorithms combined with other features such as texture and shape for improving segmentation accuracy; the other is to take sucker images from multi angles.

4 Conclusions

By evaluating seven sucker segmentation algorithms, it was concluded that:

1) ExGExR and CIVE took shorter time, which were suitable for real-time mobile targeted spray. ExG failed to segment suckers because of not taking in account of the red component of sucker color and over-extracting greenness from the background. The same situation happened to K-Lab when dealing with small size suckers. Mean shift algorithms (ExG-MS, ExGExR-MS, and CIVE-MS) had better accuracies than ExGExR and CIVE, but long time consuming (more than 9 s) made them not practical to real-time mobile targeted spray.

2) ExGExR (0.646 s and 90.3%) followed by CIVE (0.556 s and 83.7%) were suitable for real-time mobile targeted spray of sucker control from both time consuming and segmentation accuracy.

3) Future work focused on improving algorithms combining with other features and taking sucker images from multi angles.

Acknowledgments

This research was partially funded by the State Forestry Administration of China project to introduce advanced international forestry science and technology (Grant No. 2013-4-02), China Postdoctoral Science Foundation (Grant No. 2014M560897), and 2013 Technology Foundation for Selected Overseas Chinese Scholar, China Ministry of Personnel. The authors wish to thank the staff for their help in capturing pictures for this research. Awesome comments by the associate editor and reviewers greatly improved the quality of the manuscript.

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