Journal of Agricultural Machinery
Vol. 11, No. 1, Spring- Summer 2021, p. 29-42

نشریه ماشین‌های کشاورزی
جلد ۱۱، شماره ۱، نیمسال اول ۱۴۰۰، ص ۴۲-۲۹

Full Research Paper

Evaluating Histogram Equalization and Thresholding Methods for Segmentation of *Rosa Damascena* Flowers in Color Images

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Received: 07-08-2019
Accepted: 31-08-2020

Abstract

Several histogram equalization methods for enhancing the color images of *Rosa Damascena* flowers and some thresholding methods for segmentation of the flowers were examined. Images were taken outdoors at different times of day and light conditions. A factorial experiment in the form of a Completely Randomized Design with two factors of histogram equalization method at 8 levels and thresholding method at 15 levels, was implemented. Histogram equalization methods included: CHE, BBHE, BHEPL-D, DQHEPL, DSIHE, RMSHE, RSIHE, and no histogram equalization (NHE) as the control. Thresholding method levels were: Huang, Intermodes, Isodata, Li, maximum entropy, mean, minimum, moments, Otsu, percentile, Renyi's entropy, Shanbhag, Yen, constant, and global basic thresholding method. The effect of these factors on the properties of the segmented images such as the Percentage of Incorrectly Segmented Area (*PISA*), Percentage of Overlapping Area (*POA*), Percentage of Undetected Area (*PUA*), and Percentage of Detected Flowers (*PDF*) was investigated. Results of histogram equalization analysis showed that DQHEPL and NHE have the statistically significant lowest *PUA* (11.13% and 8.32%, respectively), highest *POA* (89.35% and 92.07%, respectively), and highest *PDF* (61.88% and 64.94%, respectively). Thresholding methods had a significant effect on *PISA*, *PUA*, *POA*, and *PDF*. The highest *PDF* belonged to constant, minimum, and Intermodes (75.07%, 73.08% and 74.30%, respectively) They also had the lowest *PISA* (0.35%, 1.29%, and 1.85%, respectively) and *PUA* (33.72%, 23.09%, and 15.56%, respectively). These methods had the highest *POA* (80.73%, 76.70%, and 84.67%, respectively). Hence, they are suitable methods for segmentation of *Rosa Damascena* flowers in color images.

Keywords: Histogram equalization, Image processing, Image segmentation, *Rosa Damascena*, Thresholding

Introduction

Rosa Damascena is a small plant with aromatic, light pink flowers, from *Rosaceae* family, which appears in spring and is highly cultivated all over the world, including Iran, for medicinal purposes and producing fragrances (Hajhashemi *et al.*, 2010).

Detection of the flowers in the canopy could be applied for yield estimation. It is important for farmers to estimate the quantity of a flower on the bushes at different stages of their growth so that they can make proper arrangement for harvesting labor and its distribution to specific locations in their fields. Early yield estimation can also be used to provide feedback on how crops respond to certain soil and crop management practices and to determine recommendation rates for many crop production inputs (Li *et al*., 2014). In addition, to harvest the flowers robotically, it is imperative to detect them in the canopy (Kohan *et al.*, 2011). Accordingly, different image processing methods have been developed to detect favorite objects in agriculture, which some of them are mentioned below.

Ramos *et al*. (2017) reported a non-destructive method for counting the number of fruits on a coffee branch using image processing methods. To detect the coffee fruits, homogeneous regions were segmented base on a Canny edge detector with a dynamic

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DOI: 10.22067/jam.v11i1.82330

character. Then the generated outlines were analyzed to determine whether they belonged to a coffee fruit arc or not. The points found in the previous step were adjusted into an ellipse which was evaluated for the possibility of belonging to coffee fruits. The final step consisted of placing the adjusted ellipse in the classified image for each vegetative structure, detecting a single fruit per ellipse, and counting the detected fruits according to their maturation stage.

A fast and accurate automatic segmenting method of sea cucumbers was presented by Qiao *et al.* (2017). Image fusion based on the RGB color space and the contrast limited adaptive histogram equalization method was used to increase the contrast of the sea cucumber thorns and body, respectively. An edge detection algorithm was then implemented to extract the edge of the sea cucumber thorns, as an initial contour for thorn segmentation. A rectangular contour based on the edge information was built, as the initial contour for the body segmentation. Finally, the results of the thorn and body were fused. Results showed that the mean values of Euclidean distance, sensitivity, specificity, and accuracy were 12.7, 84.51, 96.97, and 96.54, respectively. Jidong *et al.* (2016) developed a recognition method for apple fruits in a natural environment. After comparing different color spaces, I2color component in the I1I2I3color space with Otsu dynamic threshold segmentation method was chosen. Image perfection and noise removal were carried out and apple fruit contour model was established. The apple fruits were recognized by edge detection and the improved RHT transformation method, the overlapped apples and severely occluded apples by the branches and leaves were respectively separated and restored before they were recognized.

Li *et al.* (2014) reported a blueberry yield mapping system. A stepwise algorithm, termed 'color component analysis based detection' method was developed to identify blueberry fruit at different growth stages using outdoor color images. A dataset was built using manually cropped pixels from training images. Three color components, red, blue and hue, were selected using the forward feature selection algorithm and used to separate all fruits of different maturity stages from the background using different classifiers. The KNN classifier yielded the highest classification accuracy (85-98%), and the developed 'CCAD' method for blueberry was proved to be efficient.

Yamamoto *et al.* (2014) proposed an image-processing method to accurately detect individual intact tomato fruits, including mature, immature and young fruits on the plant using a conventional RGB digital camera in conjunction with machine learning approaches. In the first step, the pixel-based segmentation was conducted to roughly segment the pixels of the images into classes composed of fruits, leaves, stems, and backgrounds. The Blob-based segmentation was then conducted to eliminate misclassifications generated at the first step. At the third step, the *X*-means clustering was applied to detect individual fruits in a fruit cluster. The image segmentation was conducted based on classification models generated by machine learning approaches.

Mohamadi Monavar *et al.* (2013) considered three color spaces including RGB, HSI and YCbCr and three algorithms including threshold recognition, curvature of the image and red/green ratio in order to identify the ripe tomatoes from background under natural illumination. The average error of threshold recognition, red/green ratio and curvature of the image algorithms were 11.82%, 10.03% and 7.95% in HSI, RGB and YCbCr color spaces, respectively. Therefore, they proposed the YCbCr color space and curvature of the image algorithm as the most suitable method for recognizing fruits under natural illumination condition. Okamoto and Lee (2009) presented an image processing method to detect green citrus fruit in individual trees. The objective of the method was estimating the crop yield at the earlier stage of growth. A hyperspectral camera of 369-1042 nm was used. The algorithm was separated into two parts, i.e., pixel spectral processing and spatial processing. First, spectral processing was applied to each pixel individually for pixel segmentation, and then spatial processing was applied for green citrus fruit detection. A computer vision based method for citrus yield estimation represented by Dorj *et al.* (2017). This citrus recognition and counting algorithm was utilized the color features to detect citrus fruit on the tree. The corresponding models were developed to provide an early estimation of the citrus yield. The citrus counting algorithm consisted of converting the RGB image to HSV, thresholding, orange color detection, noise removal, watershed segmentation, and counting. The mean of the absolute error of the algorithm was determined to be 5.76% for all input images, and the main reasons for obtaining errors was due to the nearly complete occlusion, noise, shadowing, sunlight reflection on the leaves, etc. A cherry-harvesting robot was manufactured by Tanigaki *et al.* (2008). The 3-D vision sensor was equipped with red and infrared laser diodes. Both laser beams scan the object simultaneously. By processing the images from the 3-D vision sensor, the locations of the fruits and obstacles were recognized. Kohan *et al.* (2011) designed and developed a robotic harvester for *Rosa Damascena*. Flowers, which had a different color from canopy, were detected by thresholding H component of HSI color space and stereoscopic machine vision technology was implemented for locating them.

Although histogram equalization is a popular method for image enhancement and theresholding is an accepted method for segmentation, there is no comprehensive research which compare different algorithms of these methods and underline the most efficient one for agricultural use under natural light condition. In this research, several histogram equalization methods for color image enhancement and some thresholding methods for image segmentation using color information was evaluated to recognize the most precise method for detecting *Rosa Damascena*.

Material and Methods

Figure 1 shows the schematic diagram of the process. Imaging was done outdoors, in various light condition, using an A4TECH webcam with resolution of 480×640. All images were in the YCbCr color space. Each image had 3 channels (i.e. Y, Cb, and Cr) and each channel was an 8-bit grey scale image, including 256 levels from 0 to 255. First, the images were transferred to RGB color space and to enhance the color images, the same method of histogram equalization was applied to each component of RGB images individually (Rong *et al*., 2015). The images were transferred to the HSI color space and segmentation was performed by thresholding the H component. The H component is not affected by the intensity and saturation. In addition, different color of pink flowers and the green background of foliage made thresholding the H component more efficient for segmentation.

To understand the accuracy of each method, some features of the segmented images were examined. These features included: Percentage of Incorrectly Segmented Area (*PISA*), Percentage of Undetected Area (*PUDA*), Percentage of Overlapping Area (*POA*) and Percentage of Detected Flowers (*PDF*). The incorrectly segmented area included the area of the regions that were wrongly segmented and did not represent flowers. The undetected area contained parts of a flower or flowers that were not segmented. The overlapping area included the area of segmented regions that overlapped with the flowers. To normalize and calculate the percentage of the mentioned quantities, each was divided by the total area of the flowers in the image. PDF is the number of the obviously detected flowers by the algorithm, divided by the number of all the flowers in the image. Equation (1) to (4) show how these quantities calculated.

$$PISA = \frac{SNF}{AF} \times 100 \tag{1}$$

$$PUDA = \frac{ANS}{AF} \times 100 \tag{2}$$

$$POA = \frac{SOF}{AF} \times 100 \tag{3}$$

$$PDF = \frac{NS}{NF} \times 100 \qquad (4)$$

In which:
AF: area covered by flowers
SNF: area of segmented regions that do not belong to flowers
ANS: area of flowers that is not segmented
SOF: area of segmented regions which overlap with flowers in the image
NF: number of flowers in the image
NS: number of segmented flowers

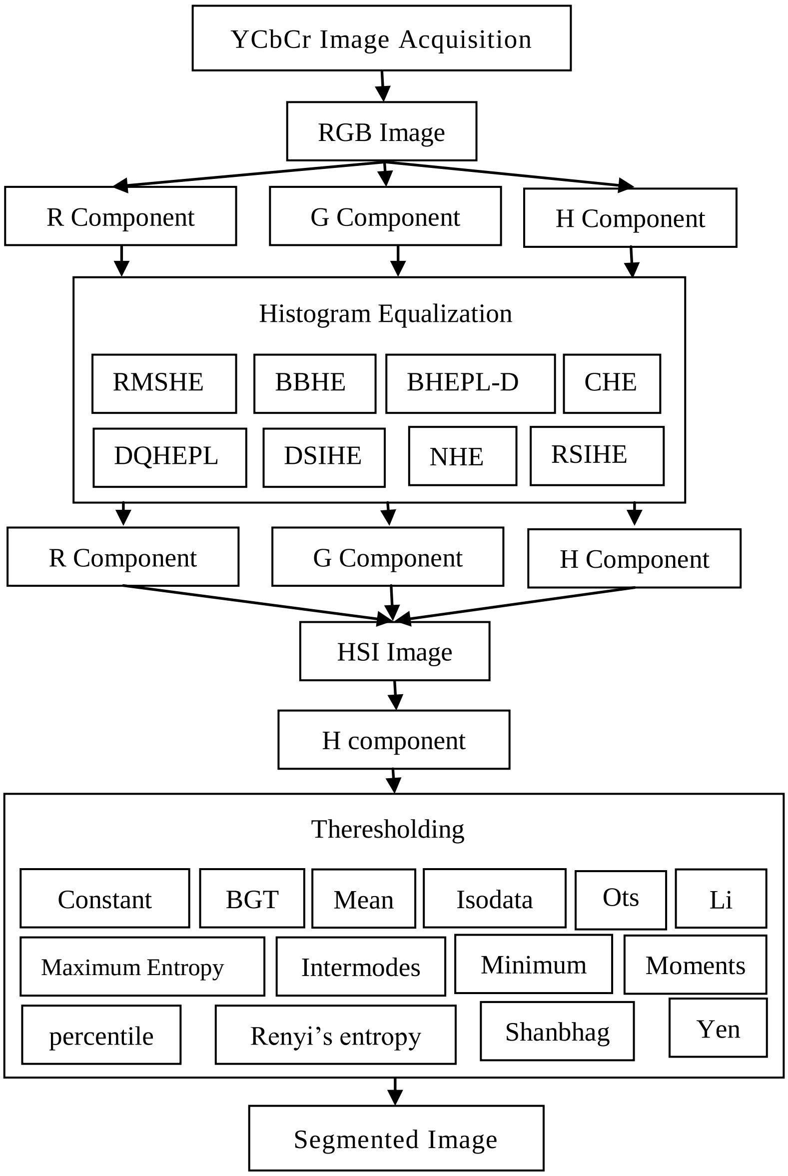

Fig.1. Schematic diagram of the process

Histogram equalization

Histogram equalization methods which examined for enhancing the components of the RGB color images included: Conventional Histogram Equalization (CHE), Brightness Preserving Bi-Histogram Equalization (BBHE), Dualistic Sub-Image Histogram Equalization (DSIHE), Recursive Sub-Image Histogram Equalization (RSIHE), Bi-Histogram Equalization Median Plateau Limit (BHEPL-D), and Dynamic Quadrants

Histogram Equalization Plateau Limit (DQHEPL).

The CHE method uses the Cumulative Distribution Function (CDF) as a transformation function, which maps the input intensity level to a new intensity level. The downside is that CHE shifts the mean intensity value, in the middle grey level of the intensity range (Farhan Khan *et al.*, 2015). To overcome this, other methods have been proposed. BBHE method divides the image histogram into two parts. In this method, the separation intensity is represented by the input mean brightness value, which is the average intensity of all the pixels that construct the input image. After this separation process, these two histograms are independently equalized. Thus the mean brightness of the resultant image will lie between the input mean and the middle grey level (Kim, 1997). DSIHE technique also decomposes the image into two equal-area sub-images based on its grey level probability density function. Then the two sub-images are equalized. The final result is obtained after the processed sub-images are composed into one image (Wang *et al*., 1999).

The extension of BBHE is RMSHE which recursively performs a separation of the input image histogram based on the mean value of the input histogram to the satisfactory number of recursion levels. Each new sub-histogram is separated based on the respective mean. As the number of recursion level increases, the mean brightness of the output image becomes closer to the input image mean brightness (Patel, 2013). Another method to preserve the brightness and natural appearance of the input images, by partitioning the histogram into more than two segments, is RSIHE (Sim and Tso, 2007) which is the extension of DSIHE method and decomposes the image into equal-area sub-images.

The Dynamic Histogram Equalization (DHE) method expands the sub-histograms to a new dynamic range by using a function depending on the number of pixels in the corresponding sub-histogram. This means that sub-histograms constituting a higher number of pixels occupy a larger range compared to other sub-histograms. However, DHE method under low light conditions suffers from intensity saturation problems and produces undesirable visual artifacts (Ibrahim and Kong, 2007). In order to avoid the intensity saturation problem, plateau-based methods have been suggested in the literature. These methods clip the peak of the histogram to some extent so that the intensity levels having high values can be prevented from expanding to a high range. By performing the clipping process, high probability regions of the histogram may be prevented from dominating over its low probability regions. Some of the plateau-based methods, are bi-histogram equalization plateau limit (BHEPL) (Ooi *et al.,* 2009), bi-histogram equalization median plateau limit (BHEPL-D) (Ooi, 2010 a), dynamic quadrants histogram equalization plateau limit (DQHEPL) (Ooi and Isa, 2010 a), and quadrants dynamic histogram equalization (QDHE) (Ooi and Isa, 2010 b).

The plateau-based methods that preserve the brightness and natural appearance of the images, are based on the assumption that the processed histograms having an intensity saturation problem are the main reason for the appearance of visual artifacts in the output images (Ooi and Isa, 2010 b).

Thresholding

Thresholding methods which were evaluated for image segmentation, included: basic global thresholding method, Huang, Intermodes, Isodata, Li, maximum entropy, mean, minimum, moments, Otsu, percentile, Renyi’s entropy, Shanbhag, Yen, and constant thresholding.

In the Basic Global Thresholding (BGT) method first, the image is divided into object and background by taking an initial threshold, in the second step, the average values of the pixels at or below the threshold and pixels above it are computed. In the third step, the threshold is set to the average of the two values found in the last step. Finally, the second and third steps are repeated until the difference of threshold in successive iterations is smaller than a predefined level (Gonzalez and Woods, 1992). “Isodata” method is a variation of the basic global thresholding except that the final step is repeated until the threshold is larger than the average brightness of the two regions (Ridler and Calvard, 1978).

Prewitt and Mendelsohn (1966) supposed that each object to be segmented creates a clear peak around the most frequent grey level value. The histogram is iteratively smoothed until only two peaks remain. In the “Intermodes” thresholding method, the midpoint of the two peaks is taken as the threshold while in the “minimum” thresholding method, the threshold is the minimum point between the peaks. The “Otsu” method searches for the threshold that minimizes intra-class variance (Otsu, 1979). Kapur *et al.* (1985) implemented the “maximum entropy” method which chooses a threshold such that the entropies of distributions above and below the threshold are maximized. This is one of the several entropy-based approaches. “Moments” method (Tsai, 1985) estimates the threshold in a way that the moments of the input image are preserved in an output image. Shanbhag (1994) considered the image as a compositum of two fuzzy sets corresponding to the two classes with membership coefficient associated with each grey level a function of its frequency of occurrence as well as its distance from the intermediate threshold selected.

“Huang’s fuzzy thresholding” uses Shannon’s entropy function (Huang and Wang, 1995). The measure of fuzziness represents the difference between the original image and its binary version. For a given threshold level, the fuzzy membership function for a pixel is defined by the absolute difference between the pixel grey level and the average grey level of the region to which it belongs, with a larger difference leading to a smaller membership value. The optimal threshold is the value that minimizes the fuzziness, as defined by Shannon’s entropy function, applied to the fuzzy membership functions.

Yen *et al.* (1995) proposed a new criterion for multilevel thresholding. The criterion is based on the consideration of two factors. The first one is the discrepancy between the thresholded and original images and the second one is the number of bits required to represent the thresholded image. Based on a new maximum correlation criterion for bi-level thresholding, the discrepancy is defined and then a cost function that takes both factors into account is proposed for multilevel thresholding. By minimizing the cost function, the classification number that the grey-levels should be classified and the threshold values can be determined automatically. In addition, the cost function is proven to possess a unique minimum under very mild conditions.

Similar to the maximum entropy method, Sahoo *et al.* (1997) proposed a new thresholding technique using Renyi's entropy. Their entropic thresholding method uses two probability distributions (object and background) derived from the original grey-level distribution of an image and includes the maximum entropy sum method and the entropic correlation method. The Li thresholding technique was based on an iterative method for minimization of cross-entropy between segmented and original image (Li and Tam, 1998). The percentile method assumes the fraction of foreground pixels to be a specific value which is 0.5 in the current research (Doyle, 1962). The “mean” method uses the mean of grey levels as the threshold. For the constant thresholding method, the color levels of the flowers in several H-component of the images were investigated and the average of 204 was selected as the constant threshold.

Statistical Design

To investigate the effect of different methods of histogram equalization and thresholding, a factorial experiment in the form of a Completely Randomized Design was implemented. The factors involved in the experiment included thresholding method and histogram equalization method at 15 and 8 levels, respectively with 20 replications. As previously mentioned, thresholding method levels included: Huang, Intermodes, Isodata, Li, maximum entropy, mean, minimum, moments, Otsu, percentile, Renyi’s entropy, Shanbhag, Yen, Basic Global Thresholding

(BGT), and thresholding with a constant value. The histogram equalization levels were CHE, BBHE, BHEPL-D, DQHEPL, DSIHE, RMSHE, RSIHE and No Histogram Equalization (NHE) as the control. The factorial experiment was performed on ten images that were selected arbitrarily. The images applied to determine the value of the constant threshold were not used in the factorial experiment.

Results and Discussion

As described in the previous sections, after taking image, the histogram of each component of the RGB image was processed individualy. Afterward the components joined together to form a color image with a higher quality. Figures 2, 3 and 4 show the histogram equalization results using different methods under different light conditions.

After applying histogram equalization to each component and corporating them again, the color space of the image transformed to HSI. Figure 5 shows the result of This transformation and extracting the H component. Figure 5a is the original image, which, as can be seen, does not have a good quality because of poor lighting situation. Figure 5b is the same image, which quality is improved by the CHE method. In this image, flowers are easily visible.

Fig.2. Contrast equalization using different methods on an 8-bit image with the mean intensity of 89.68 and Standard Deviation of 68.60; a) NHE, b) BBHE, c) BHEPL-D, d) CHE, e) DQHEPL, f) DSIHE, g) RMSHE and h) RSIHE

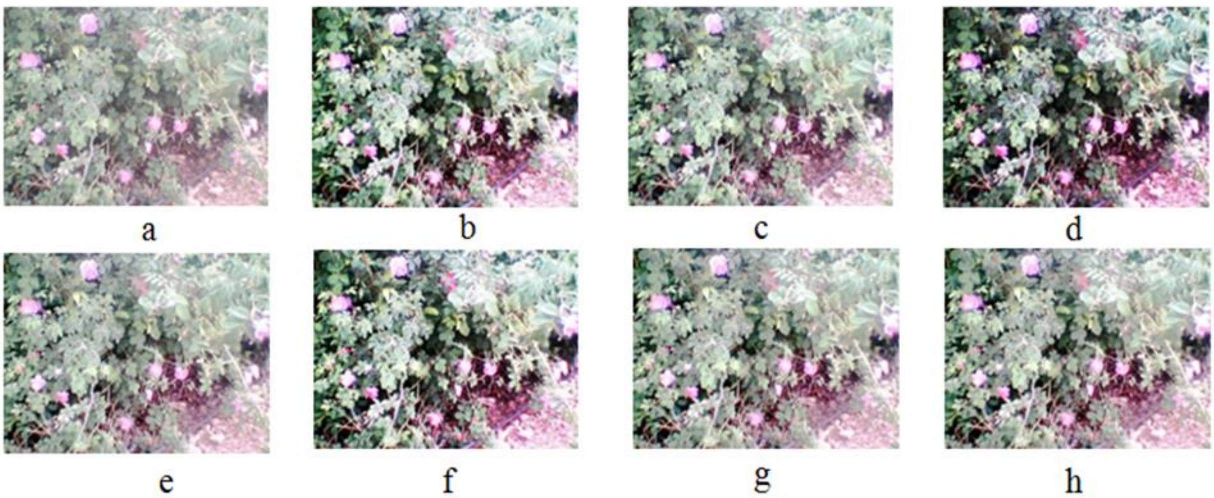

Fig.3. Contrast equalization using different methods on an 8-bit image with the mean intensity of 176.2 and Standard Deviation of 40.99; a) NHE, b) BBHE, c) BHEPL-D; d) CHE; e) DQHEPL, f) DSIHE, g) RMSHE and h) RSIHE

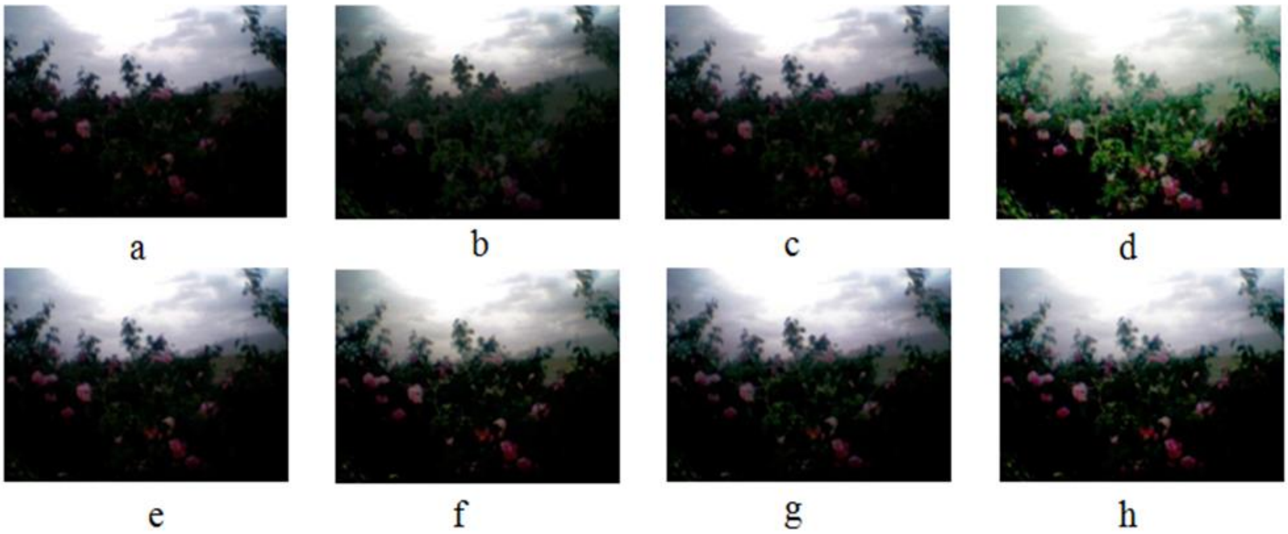

Fig.4. Contrast equalization using different methods on an 8-bit image with the mean intensity of 61.42 and Standard Deviation of 82.71; a) NHE, b) BBHE, c) BHEPL-D, d) CHE, e) DQHEPL, f) DSIHE, g) RMSHE and h) RSIHE

Figure 5c is the H component of Figure 5a which is obtained after transforming this image from RGB to HSI color space. As seen, saturation and intensity do not affect the H component, and the position of the flowers is clearly evident because the H component only contains color information.

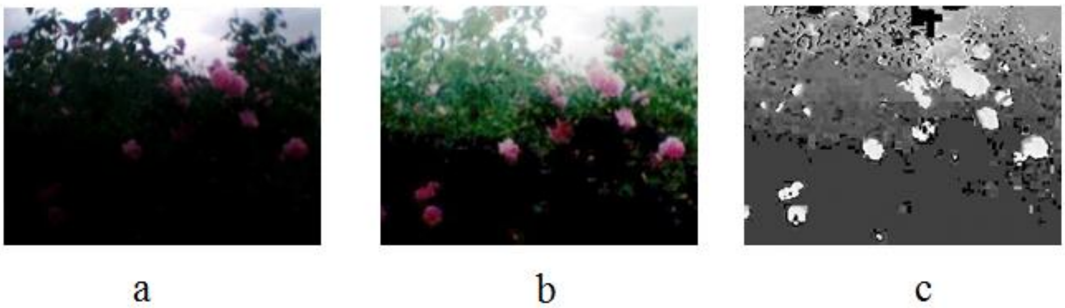

Fig. 5. a) RGB image with poor light condition, b) Image **a** after histogram equalization using CHE method and c) H component of image **a** after conversion from RGB to HSI color space

The final step was theresholding. Figure 6 shows the results of thresholding using different methods. No histogram equalization has been applied to this image.

Figure 7 illustrates the properties of the segmented image visually. Figure 7a, is the reference image and the regions of the flowers are manually specified. Figure 7b shows the result of the segmentation by the software. Figure 7c shows incorrectly segmented areas that do not belong to the flowers, Figure 7d shows undetected areas and Figure 7e shows the areas that are both segmented by the software and belong to the flowers

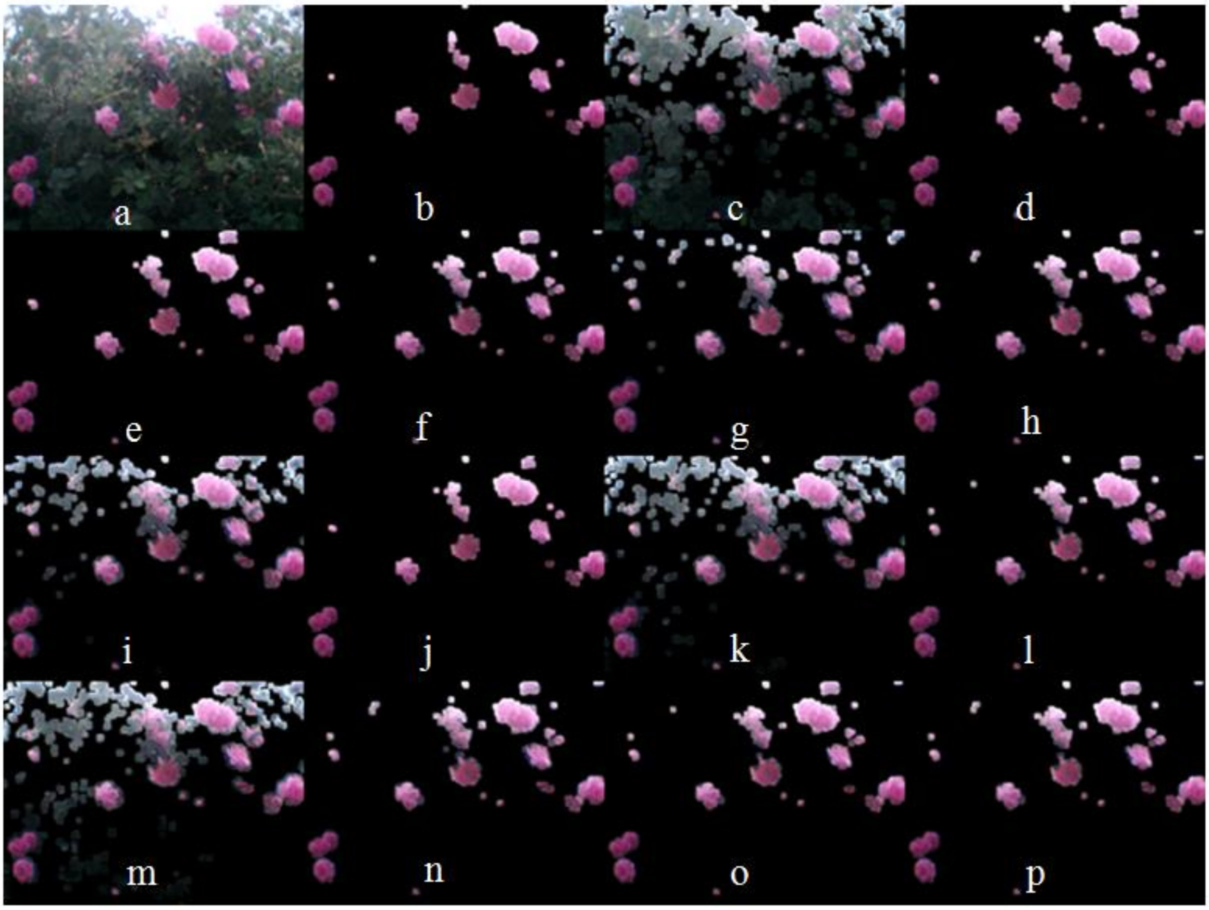

Fig.6. The result of thresholding using different methods: a) Original image with no histogram equalization, b) Constant, c) BGT, d) Huang, e) Intermodes, f) Isodata, g) Li, h) Maximum entropy, i) Mean, j) Minimum, k) Moments, l) Otsu, m) Percentile, n) Renyi’s entropy, o) Shanbhag and p) Yen

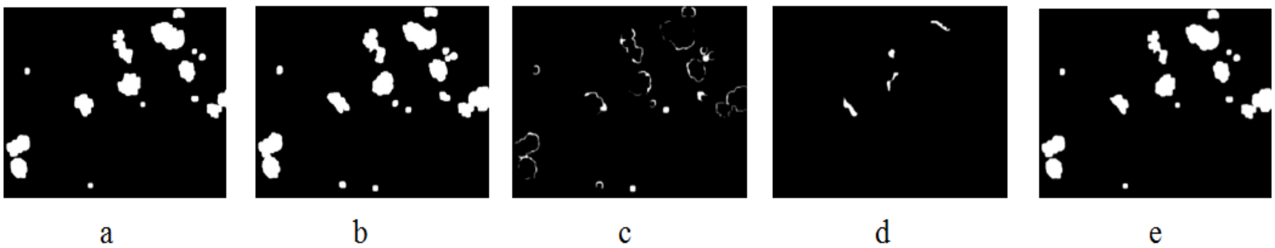

Fig.7. Properties of the segmented image in comparison with the reference image: a) Reference Image, b) Segmented image, c) Incorrectly segmented area, d) Undetected area and e) Overlapping area

Statistical methods applied to determine the best method of histogram equalization and theresholding. Table 1 shows the results of ANOVA for the effect of thresholding method and contrast equalization method on different properties. In cases where analysis of variance showed a significant difference, Duncan’s Multiple Range Test at the 5% level was used. The results are shown in Table 2 and Table 3.

Table 1- ANOVA results for the effect of thresholding method and contrast equalization method on different properties

Source	PISA		PUA		POA		PDF	
	F	Sig.	F	Sig.	F	Sig.	F	Sig.
CE	0.838^{ns}	0.555	18.622*	0.000	17.947*	0.000	25.170*	0.000
T	13.317*	0.000	15.281*	0.000	6.427*	0.000	27.871*	0.000
CE*T	0.127^{ns}	1.000	0.086^{ns}	1.000	0.069^{ns}	1.000	0.510^{ns}	1.000

ns: No significant difference, * Significantly different at the 99% confidence interval

According to Table 1, the histogram equalization methods did not have a significant effect on the *PISA*. As shown in Table 2, NHE and DQHEPL had the lowest *PUA*. This is while NHE, DQHEPL, and BHEPL-D showed the highest *POA*. NHE, BHEPL-D, RSIHE, DQHEPL, and RMSHE showed the highest *PDF*. Therefore, NHE and DQHEPL, which had the lowest *PUA*, the highest *POA*, and the highest *PDF*, are appropriate methods for equalizing the histogram.

According to Table 3, the constant and minimum thresholding methods had the lowest *PISA*, but constant thresholding yielded the most *PUA*. The *PUA* of the minimum thresholding method was lower than constant thresholding one level, so it also had a relatively high value. The Li method had the least *PUA* and did not have a significant difference with Huang, Intermodes, Isodata, maximum entropy, mean, moments, Otsu, percentile, Renyi’s entropy, Yen, and BGT.

Table 2- Comparison of the means for the effects of histogram equalization method on the studied factors

Method	PUA	POA	PDF
BBHE	20.99c	79.67a	50.58b
BHEPL_D	11.84b	88.84bc	64.87d
CHE	20.56c	80.29a	41.48a
DQHEPL	11.13ab	89.35bc	61.88d
DSIHE	20.34c	80.23a	55.79c
NHE	8.32a*	92.07c	64.94d
RMSHE	12.73b	88.02b	61.58d
RSIHE	12.43b	88.27b	64.12d

*Same lowercase letters show no significant difference between factors in each column at the 5% level using Duncan’s Multiple Range Test.

Table 3- Comparison of the Means for the effects of Thresholding Method on the studied factors

Method	PISA	PUA	POA	PDF
BGT	4.31efg	11.52ab	88.47de	53.21d
Constant	0.35a	33.72e	80.73ab	75.07e
Huang	3.63def	14.63abc	85.14bcde	62.94efg
Intermodes	1.85bc	15.56bc	84.67bcd	74.30he
Isodata	4.11efg	11.71ab	88.32de	57.00de
Li	5.89h	9.77a	90.22e	43.51ab
Maximum entropy	2.54bcd	13.17abc	88.33de	65.50g
Mean	5.18gh	10.78ab	89.21de	42.01ab
Minimum	1.29ab	23.09d	76.70a	73.08he
Moments	4.45fg	11.38ab	80.44ab	46.25bc
Otsu	3.96efg	11.80ab	88.23de	57.98def
Percentile	5.87h	10.74ab	89.25de	38.33a
Renyi’s entropy	2.46bcd	12.97abc	88.89de	63.93fg
Shanbhag	2.98cde	17.66c	82.37bc	51.59cd
Yen	2.24bc	13.36abc	86.69cde	67.64gh

Same lowercase letters show no significant difference between factors in each column at the 5% level using Duncan’s Multiple Range Test.

Observing the *POA* column in Table 3, it is obvious that the Li method had the highest value of *POA* and did not have a significant difference with mean, percentile, Renyi's entropy, Isodata, maximum entropy, Yen, Otsu, Huang and BGT method. But these methods yielded a very high *PISA*, which has caused many regions other than flowers to be segmented incorrectly and the position of the flowers could not be detected well enough. The highest *PDF* was achieved by the constant thresholding method and did not show a significant difference with Intermodes and minimum methods. Although *PUA* is high, and *POA* is low in recently mentioned methods, it should be considered that properly segmented regions are higher and the position of the flowers is well defined. Therefore, the best methods for thresholding are constant, Intermodes and minimum.

It can be seen in Table 4 that the highest detection success rate was 85.66 belonging to constant thresholding method and original images without histogram equalization.

Table 4- Average of PDFs in different methods

Thresholding method	Histogram equalization method							
	BBHE	**BHEPL-D**	**CHE**	**DQHEPL**	**DSIHE**	**NHE**	**RMSHE**	**RSIHE**
Constant	69.24	81.19	63.70	80.52	72.06	85.66	73.67	74.53
BGT	40.28	63.08	39.40	63.85	50.97	52.28	59.79	56.02
Huang	58.05	64.98	42.38	61.13	57.51	76.03	70.57	72.88
Intermode	72.23	78.57	48.57	83.00	69.99	87.31	77.20	77.56
IsoData	50.31	61.57	38.67	63.57	51.33	60.49	62.07	68.01
Li	32.56	50.39	24.34	51.98	43.69	52.66	42.32	50.15
MaxEntropy	52.79	76.71	46.74	71.71	61.87	66.60	72.60	74.99
Mean	36.06	47.15	33.66	39.84	40.22	50.64	43.30	45.17
Minimum	73.50	81.58	51.32	71.73	76.80	80.32	71.66	77.76
Moments	43.72	53.51	34.75	56.39	39.45	48.32	45.93	47.91
Otsu	46.08	64.75	39.58	63.54	54.50	69.37	62.65	63.41
Percentile	37.19	40.82	29.40	36.45	38.80	45.68	37.47	40.80
RenyiEntropy	43.56	75.83	43.35	69.84	62.38	68.95	73.05	74.46
Shanbhag	41.36	61.42	35.81	48.01	50.10	58.44	53.07	64.48
Yen	61.79	71.57	50.50	66.67	67.21	71.31	78.37	73.69

Kohan *et al.* (2011) reported a 98% success rate. The higher detection rate was because of the optimum light condition and imaging conditions there, and the complementary image processing which had been performed.

Ramos *et al*. (2017) reported 80.99% average visibility percentage for counted fruits in images of coffee branches. The method developed by Jidong *et al.* (2016) for recognizing apple fruits in the natural environment resulted in detection percentages of 100%, 100%, and 86%, respectively, for nonoccluded fruit, overlapping fruit and fruit occluded by branches and leaves. The image-processing method proposed by Yamamoto *et al*. (2014) detected 80% of all tomato fruits in the test images. The detection success rate of the image processing method presented by Okamoto and Lee (2009) for detecting green citrus fruit was 70-85%, depending on citrus varieties. The fruit detection tests revealed that 80-89% of the fruits in the foreground of the validation set were identified correctly, though many occluded or highly contrasted fruits were identified incorrectly. The percentage of cherry fruit visibility with the 3-D vision sensor reported by Tanigaki *et al.* (2008) was 59%. Different detection rates, of the mentioned investigations, were due to the use of different image processing methods on crops.

Conclusions

Several methods of histograms equalization for increasing the quality of color images and some thresholding methods for segmentation of *Rosa Damascena* flowers were evaluated. After examining various histogram processing methods, it was found that the statically significant lowest percentage of undetected area (*PUA*=11.13%) and the highest percentage of overlapping area (*POA*=89.35%) as well as the highest percentage of detected flowers (*PDF*=61.88%) belonged to the DQHEPL method, and did not show a significant difference with images without histogram equalization or NHE (PUA=8.32%, POA=92.07%, PDF=64.94%). The constant thresholding method shows the highest number of correctly segmented which was 75.07% and did not have a significant difference with minimum (PDF=73.08%) and Intermode methods (PDF=74.30%). Therefore, these methods are suitable for segmentation of the images. But due to the fact that one of the most important issues, with machine vision is reduction of computation time, in order to increase the processing speed, it is recommended that histogram equalization should not be performed and the constant thresholding of the H component of HSI color space be used for segmentation of *Rosa Damascena* flowers.

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نشریه ماشین‌های کشاورزی
جلد ۱۱، شماره ۱، نیمسال اول ۱۴۰۰، ص ۴۲-۲۹

Journal of Agricultural Machinery
Vol. 11, No. 1, Spring- Summer 2021, p. 29-42

مقاله علمی-پژوهشی

بررسی روش‌های متعادل‌سازی هیستوگرام و آستانه‌گیری برای بخش‌بندی گل محمدی در تصاویر رنگی

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تاریخ دریافت: ۱۳۹۸/۰۵/۱۶
تاریخ پذیرش: ۱۳۹۹/۰۶/۱۰

چکیده

به‌منظور افزایش دقت بخش‌بندی تصاویر گل محمدی، چند روش متعادل‌سازی هیستوگرام برای بهبود کیفیت تصاویر رنگی این گل‌ها و چند روش آستانه‌گیری برای بخش‌بندی گل‌های مذکور در تصویر، مورد بررسی قرار گرفت. قابل ذکر است که تصویربرداری در فضای باز و ساعات مختلف روز و شرایط متفاوتی از شدت نور انجام گرفت. برای بررسی دقیق‌تر، یک آزمایش فاکتوریل در قالب یک طرح کاملاً تصادفی با دو عامل روش متعادل‌سازی هیستوگرام، در ۸ سطح و روش آستانه‌گیری، در ۱۵ سطح به‌کار گرفته شد. روش‌های متعادل‌سازی هیستوگرام عبارت بودند از: CHE, BBHE, BHEPL-D, DQHEPL, DSIHE, RMSHE, RSIHE و تیمار شاهد بدون متعادل‌سازی هیستوگرام (NHE). همچنین روش‌های آستانه‌گیری عبارت بودند از: Huang, Intermodes, Isodata, Li, maximum entropy, mean, minimum, moments, Otsu, percentile, Renyi’s entropy, Shanbhag, Yen, constant و global basic thresholding method. تاثیر این دو عامل بر خصوصیات تصویر بخش‌بندی شده از قبیل: درصد سطوحی که به اشتباه بخش‌بندی شده‌اند (PISA)، درصد هم‌پوشانی سطوح (POA)، درصد سطوحی که تشخیص داده نشده‌اند (PUA) و درصد سطوح تشخیص داده شده گل‌ها (PDF) مورد بررسی قرار گرفت. نتیجه روش‌های متعادل‌سازی هیستوگرام نشان داد که DQHEPL و NHE پایین‌ترین میزان PUA (به‌ترتیب ۱۱/۱۳٪ و ۸/۳۲٪)، بالاترین POA (به‌ترتیب ۸۹/۳۵٪ و ۹۲/۰۷٪) و بالاترین PDF (به‌ترتیب ۶۱/۸۸٪ و ۶۴/۹۴٪) را از لحاظ آماری دارا می‌باشند. روش‌های آستانه‌گیری تاثیر معنی‌داری بر PISA, PUA, POA و PDF داشتند. بزرگ‌ترین مقادیر PDF به روش آستانه‌گیری constant، minimum و Intremodes (به‌ترتیب ۷۵/۰۷٪، ۷۳/۰۸٪ و ۷۴/۳۰٪)، همچنین کمترین مقدار PISA مربوط به این موارد بود (به‌ترتیب ۰/۳۵٪، ۱/۲۹٪ و ۰/۳۵٪) و PUA (به‌ترتیب ۳۳/۷۲٪، ۲۳/۰۹٪ و ۱۵/۵۶٪). این روش‌ها بزرگ‌ترین مقدار POA را نشان دادند (به‌ترتیب ۸۰/۷۳٪، ۷۶/۷۰٪ و ۸۴/۶۷٪). لذا روش‌های مناسبی برای بخش‌بندی گل محمدی در تصویر رنگی محسوب می‌گردند.

واژه‌های کلیدی: آستانه‌گیری، بخش‌بندی تصویر، پردازش تصویر، تعدیل هیستوگرام، گل محمدی

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DOI: 10.22067/jam.v11i1.82330