Development of suitable algorithm for recognition and locating saffron flower using machine vision

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DEVELOPMENT OF SUITABLE ALGORITHM FOR RECOGNITION AND LOCATING SAFFRON FLOWER USING MACHINE VISION

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ABSTRACT

Saffron**(** Sativus Crocus) is one of the most invaluable agricultural commodities which are usually consumed as a spice. There are many medicine and industrial products made from this plant. Currently saffron is harvested manually and this process is difficult and exhausting job. Also human contact to its limpsy and delicate flowers can cause pollution that decreases the product quality. The quality of saffron could enhance if automation technologies were enrolled in the production. The first step for automation the saffron harvesting is to employ autonomous vision systems to be able to distinguish the flowers among the other plants, green leaves and surrounding soil. An appropriate algorithm was developed in this study based on image processing techniques to recognize and locate the saffron flowers in the field. Color features of the images in HSI and YC_rC_b color spaces were used to detect the flowers. High pass filters were used to eliminate the noises from the segmented images. Overlapping of separate flowers were modified using dilation and erosion technique and the separated flowers were labeled. Proposed flower harvester was considered to pick the flowers using vacuum snapper. Therefore center of the flower area was calculated by the algorithm as the location of the plant which must be detected by the harvesting machine. False and correct detection of the plants were measured using new images comprising saffron, green leaves, weeds and background soil. Accuracy of recognition algorithm in locating the saffron flowers was gained to 94.5% for HSI color space and 98.7% when YC_rC_b color space was used.

Keywords: Saffron, Machine vision , Harvester

Introduction

Saffron (Crocus sativus) has been used as a seasoning, fragrance, dye, and medicine for more than 3,000 years. The world's most expensive spice by weight (Abdullaev, 2002) saffron consists of stigmas plucked from the saffron crocus. The resulting dried "threads" are distinguished by their bitter taste, hay-like fragrance, and slight metallic notes.

This species is a sterile triploid that produced annual replacement corms and is propagated solely from these corms (Assimopoulou et al. 2005.). After aestivating in spring, the plant sends up five to eleven narrow and nearly vertical green leaves, each up to 40 cm (16 in) in length. In autumn, purple buds appear. Only in October, after most other flowering plants have released their seeds, do its brilliantly hued flowers develop; they range from a light pastel shade of lilac to a darker and more striated mauve (Davies et al. 2005) Upon flowering, plants average less than 30 cm (12 in) in height.

Saffron is native to Southwest Asia (Assimopoulou, et al. 2005). Saffron was first cultivated in Greece (Courtney, 2009) Iran, Spain, India, Greece, Azerbaijan, Morocco, and Italy dominate the world saffron harvest, with Iran and Spain alone producing 80% of the world crop. Saffron production requires intensive hand labour, particularly for flower picking and stigma separation.

Increasing labor costs have turned production unprofitable despite its high market price (Negbi, 1999). The high cost of saffron is due to the difficulty of manually

extracting large numbers of minute stigmas. Nowadays, almost all the saffron manipulations are carried out manually. Some machines for saffron bulb planting have been developed (Mohammad, 2006). To turn saffron production profitable, the most labor-requiring steps should be mechanized (Molina, et al. 2005).
The first and most important step to design an automated system to harvest saffron flower is development of a suitable algorithm to recognize and allocate the flower in the field. This algorithm must separate the flower from other objects such as soil, saffron leaves, weeds, brushwood and other possible unacceptable materials. Color is an effective descriptor to enhance an object in an image thereby simplifying object identification and extraction from an image (Bulanon et al. 2002).
This system must take into account the appearance of highlights and shadows in the saffron field, the algorithm must remove the effect of lights and shadows to have a successful recognition. In this study, a machine vision based system was developed for a saffron harvesting robot. Proposed saffron harvester was considered to recognize the flower then locate it, after that the picker arm of the harvester stands above the flower in a vertical position and picks the flower using a vacuum snapper system.
Gracia et al. (2009) used a vision based system and image analysis to determine the optimal cutting point of the saffron flower to obtain the stigmas. The computer program processes the flower image and sends the computed value to a driver that positions a simple mechanical cutting system to make a clean cut of the saffron flower.
Bulanon et al. (2002) developed an algorithm for the automatic recognition of Fuji apples on the tree; they enhanced the fruit from other objects in image using the red color difference.
Huang and Lee (2010) developed a vision-guided grasping system for Phalaenopsis tissue culture plantlets. They employed an image processing algorithm to determine the suitable grasping point on the plant root.
Hemming and Rath (2001) used digital image analysis to develop an identification system for weeds in crops. Their experiments showed that color features were successfully for the segmentation procedure of plants from soil and help to increase the classification.
Chien and Lin (2002) proposed an image-processing algorithm based on the elliptical Hough transform to determine position, orientation, and leaf area of seedling leaves from a top-view image.
Camargo et al. (2009) developed an image-processing based algorithm to automatically identify plant disease visual symptoms.
There is no study to develop a suitable machine to harvest saffron from the field, therefore the objective of this work was to develop an algorithm to automatically recognize and allocate a center of saffron flower in the field condition.

Materials and methods

The color images were captured from saffron fields of Istahban in Fars province of Iran. A CCD camera was used and mounted vertically at the distance of 30 cm above the flowers. Saffron flowers were selected randomly. RGB images were taken under natural daylight condition (sunlight, shaded and cloudy conditions) Images were then transferred to computer and were analyzed using image processing toolbox version 6.00 for MATLAB version7 (Mathworks, 2007).
Twenty images were used for the image analysis and 50 images were used to assess the algorithm.

The color properties of images were used to analyze because of good difference between saffron flower and other objects in the images. Two algorithms were developed, the flowcharts in Fig. 1 shows the two algorithms to automatically determine the optimal threshold and recognize the saffron flower. In the first algorithm, RGB images were converted to HSI color space which has three components: hue (H) is what we perceive as color, saturation (S) and intensity (I).

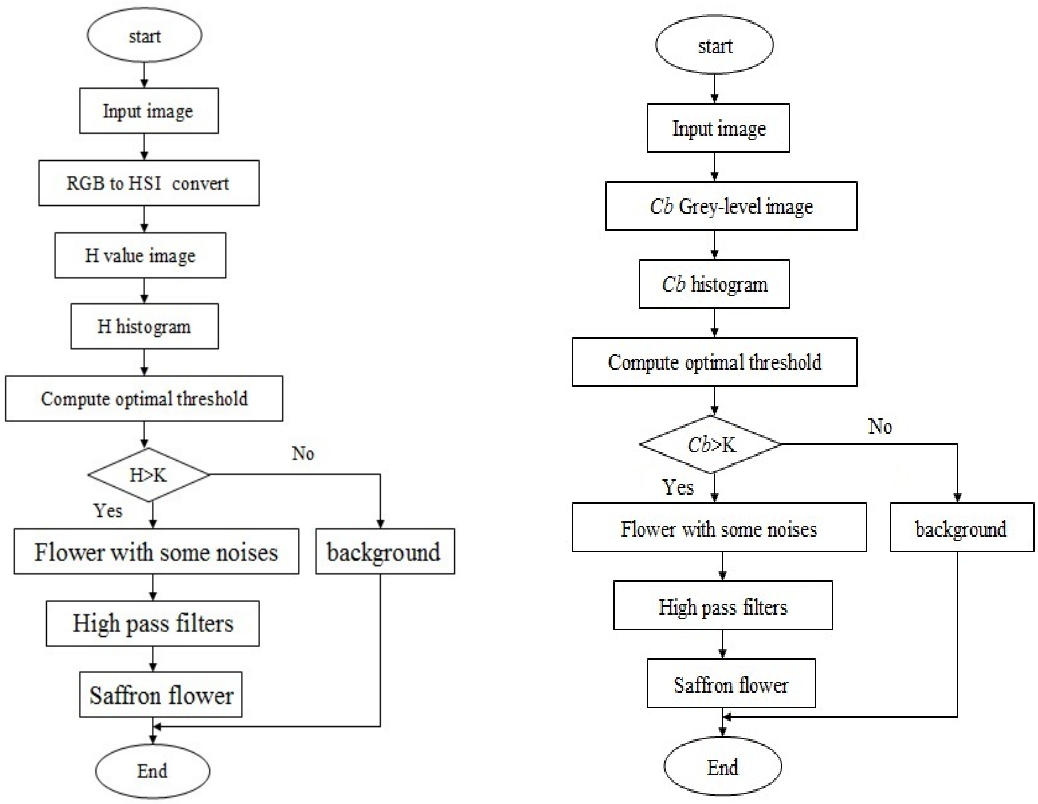

Figure 1. Flowchart of the recognition algorithm; right: HSI space, left: blue color difference (C_b).

Intensity is sometimes substituted with brightness and then it is known as HSB. The HSI color space closely approximates the behavior of the human eye. As images were taken in different lighting conditions, the algorithm must have the ability to remove this bad effect. In HSI color space it is possible to separate the color from brightness so it is a good space to exclude lighting effect from the color of objects. The RGB to HSI conversion is defined by the following equations:

$$H = \cos^{-1}\left\{ \frac{\frac{1}{2}\left[(R-G)+(R-B)\right]}{\left[(R-G)^2+(R-B)(G-B)\right]^{1/2}} \right\} \tag{1}$$

$$S = 1 - \frac{3}{(R+G+B)}\left[\min(R,G,B)\right] \tag{2}$$

$$I = \frac{1}{3}(R+G+B) \tag{3}$$

H, S and I vary from 0 to 1, where 1 represents the largest saturation and value. The next step was to separate flower from other objects. Figure 2 shows an example of a bimodal histogram with hue value ranging from 0 to 1. The histogram is composed of the background distribution and the object distribution. In this work, soil, leaves and weeds belong to the background while the flower is the object. The probability of class occurrence and the class mean of the flower and background, respectively, are given by:

$$w_F = \sum_{i=1}^{K} p_i \tag{4}$$

$$w_B = \sum_{i=K+1}^{L} p_i = 1 - w_F \tag{5}$$

$$\mu_F = \sum_{i=1}^{K} \frac{ip_i}{w_F} \tag{6}$$

$$\mu_B = \sum_{i=K+1}^{L} \frac{ip_i}{w_B} \tag{7}$$

Where: w_F is the saffron flower class occurrence; w_B is the background class occurrence; μ_F is the flower class mean, μ_B is the background class mean; p_i is the number of pixels at hue value i divided by the total number of image pixels; L is the total number of hue values; and k is the threshold that separates the Saffron flower and the background. The total mean level μ_T of the histogram is:

$$\mu_T = \sum_{i=1}^{L} ip_i \tag{8}$$

The threshold k can be selected by finding the lowest point between the two distributions.

The color properties used in the second algorithm were; luminance (Y) and blue color difference (C_b). The following equations were used to convert RGB data to luminance and color difference signal:

$$Y = 0.3R + 0.6G + 0.1B \tag{9}$$

$$C_r = R - Y \tag{10}$$

$$C_g = G - Y \tag{11}$$

$$C_b = B - Y \tag{12}$$

Where R, G and B are the red, green and blue color intensity values ranging from 0 to 255. Primitive tests showed that red and green color differences (C_r and C_g) did not lead to useful results in this case.

Each of the main components of the RGB image will increase when ambient luminance increases. Since the sum of the coefficients of R, G and B values in C_b equation (Equ. 12) is zero so the blue chrominance value (C_b) would be insensitive to this luminance increase. It means that the situation of the flower in light or shadow does not affect the segmentation result.

$$C_b = B - Y = 0.9B - 0.3R - 0.6G = 0.9(B + M) - 0.3(R + M) - 0.6(G + M) \qquad (13)$$

The formulas of probability of class occurrence and the class mean of the flower and background are the same as the first procedure except; p_i is the number of pixels grey-level i divided by the total number of image pixels and L is the total number of grey-level intensities. Figure 2 shows examples of H and C_b value distribution histograms where H value ranging from 0 to 1 and this range is 0 to 255 for C_b. In both algorithm, some noises remain in the images after conversion to binary images using thresholds.

High pass filters and morphological operations were performed to omit the small objects misclassified as flowers. Due to these operations no pixel of background was remained in the binary images. In some images saffron flowers had overlaps. This problem was modified using dilation and erosion techniques.

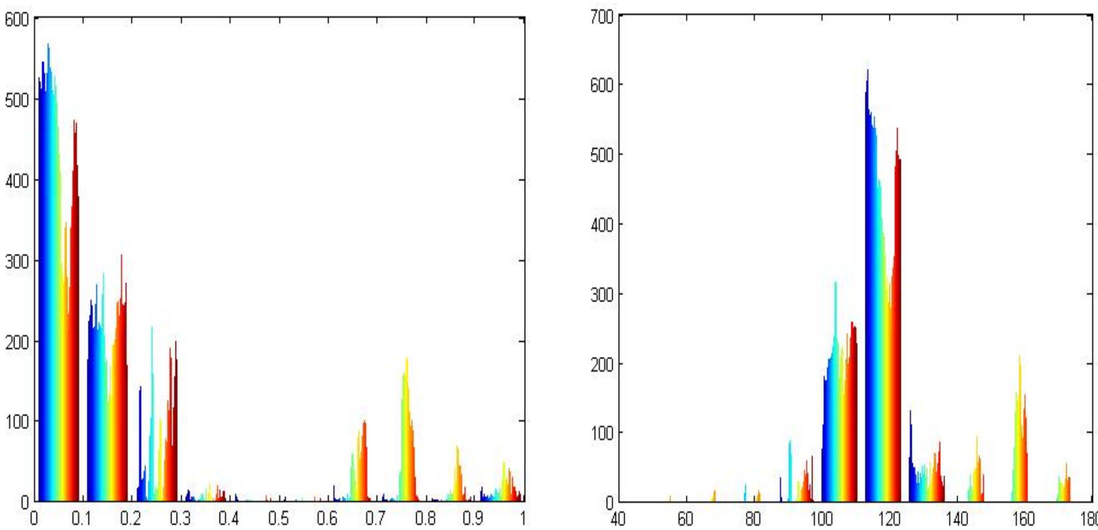

Figure 2. Image Histograms; right: C_b values, left: H values

The separated flowers were labeled. Finally the center of area for each labeled object was determined. The algorithms were evaluated by measuring the percentage of correct segmentation rate (CSR) of the pixels. The CSR was defined as the ratio of number of flower pixels correctly segmented as flower to the number of flower pixels. Incorrect classification rate (ISR) was defined as the ratio of number of flower pixels incorrectly classified as other objects to the total number of flower pixels.

Results and discussion

To select the best color component that provide the optimum segmentation, the pixel values of saffron flower, leaf, soil and residues were compared for each color component. The color components whit the most significant difference between flower and other objects were selected. T-test mean compare was developed. Results are shown in table 1.

Based on the table 1, the flower shows the most significant difference with leaf, soil and other residues when C_b and H color component are used. This is why we used these two components to develop the algorithms. Also it is seen from the aforementioned table that there is high significant difference between leaf and other objects of image in C_g component so it seems that this color component is useful for Weed Identification under Field Conditions. Figure 3 shows an example of the result of the segmentation and flower recognition using optimal threshold. The flower has been recognized and separated from other objects in the image. Table 2 shows the segmentation results in two different procedures.

Table 1. T-test results for determination of the color components lead to the best segmentation algorithm

H	Flower	Soil	Leaf
Flower	---	**	*
Soil	**	---	ns
Leaf	*	ns	---

S	Flower	Soil	Leaf
Flower	---	ns	ns
Soil	ns	---	ns
Leaf	ns	ns	---

v	Flower	Soil	Leaf
Flower	---	ns	ns
Soil	ns	---	ns
Leaf	ns	ns	---

C_r	Flower	Soil	Leaf
Flower	---	ns	ns
Soil	ns	---	ns
Leaf	ns	ns	---

C_g	Flower	Soil	Leaf
Flower	---	ns	**
Soil	ns	---	**
Leaf	**	**	---

C_b	Flower	Soil	Leaf
Flower	---	**	*
Soil	**	---	ns
Leaf	*	ns	---

ns : Corresponding to no significant difference.
** : Corresponding to 1% probability.
*: Corresponding to 5% probability.
Soil sits instead of soil and other residues

The CSR for HSI method was 94.5% while this accuracy rate was 98.7% for YCrCb method. Results showed that the thresholds used to segment images under different lighting conditions are the same because the algorithm uses H color value in HSI color space and C_b value that remove the effect of brightness in images. This indicates that the algorithm is not dependent to the condition images taken and can be useful in different daylights.

Table 2. Segmentation results of the HSI and YC_rC_b methods

			Soil and residue	Green leaves	Saffron flower
Method	HSI	Soil and residue	97.1	1.8	1.1
		Green leaves	1.3	98.3	0.4
		Saffron flower	2.4	3.1	94.5
	YC_rC_b	Soil and residue	97.4	1.6	1
		Green leaves	1.5	98.1	0.4
		Saffron flower	0.6	0.7	98.7

a

e

f

g

b

c

d

Figure 3. Example of saffron flower recognition using two different method: (a) original color image of saffron; (b) Hue component image; (c) binary image using Hue value threshold; (d) final segmented image after noise removal and morphological operations; (e) Blue color difference (C_b) component of the image; (f) binary image using threshold on blue color difference; (g) final segmented image using blue color difference method.

The main objective of saffron flower detection is to design a flower harvesting machine capable of snapping the flowers with the knowledge of their location. Therefore a special spot must be defined for the robot as the location of the flower. Centeroid (center of the area) of the flower was considered as an estimate for the location of peduncle.

Peduncle detection error (PDE) was defined as the difference between the position of flower centroid respect to peduncle. PDE was determined using equation (14).

$$PDE = \sqrt{(X_c - X_a)^2 + (Y_c - Y_a)^2} \tag{14}$$

Where X_c and Y_c are the coordinates of flower centroid in the images and X_c, Y_c are actual center of flower where peduncle connected to flower. The position of actual center was manually marked on the images and PDE was determined for 20 images of saffron flowers. Both methods had almost the same PDE. The results of peduncle detection error based on the two aforementioned methods (H and C_b) are given in table 3.

Table 3. peduncle detection error (PDE)

Method	PDE (mm)	
	Mean	S.d.
H	1.987	0.488
C_b	1.992	0.651

Negligible difference between the methods can be referred to different detected area caused by differences between the CSR of the methods.

Although the main source of variation in PDE in both methods was due to the inclination of flower respect to imaging direction.

It was seen that when images taken accurately perpendicular to flower, PDE error diminish even to zero. Thus it can be recommended to consider

Conclusion

Two different algorithm for saffron flower detection was developed based on the hue (H) and blue color difference (C_b) components of the images. The accuracy of the methods verified while C_b component yielded better detection result. In the next step, position of the flower was addressed based on the centroid of the flower. Results showed that when images were taken perpendicularly to the flower, the centroid can be considered as a good reference for further use by harvesting machine. It is recommended that if more accurate positioning of peduncle or stigma is aimed, some equipment can be added to image acquisition system to comb and straight up the flowers.

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