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Integration of Color Features and Artificial Neural Networks for In-field Recognition of Saffron Flower

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ABSTRACT-Manual harvesting of saffron as a laborious and exhausting job; it not only raises production costs, but also reduces the quality due to contaminations. Saffron quality could be enhanced if automated harvesting is substituted. As the main step towards designing a saffron harvester robot, an appropriate algorithm was developed in this study based on image processing techniques to recognize and locate 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 noise from the segmented images. Partial occlusion of flowers was modified using erosion and dilation operations. Separated flowers were then labeled. The proposed flower harvester was to pick flowers using a vacuum snapper. Therefore, the center of the flower area was calculated by the algorithm as the location of the plant to be detected by the harvesting machine. Correct flower detection of the algorithm was measured using natural images comprising saffron, green leaves, weeds and background soil. The recognition algorithm's accuracy to locate saffron flowers was 96.4% and 98.7% when HSI and YC_rC_b color spaces were used. Final decision making subroutines utilize artificial neural networks (ANNs) to increase the recognition accuracy. A correct detection rate of 100% was achieved when the ANN approach was employed.

Keywords: Artificial neural networks, Saffron, Machine vision, Harvester

INTRODUCTION

Saffron, the world's most expensive spice by weight, consists of stigmas plucked from the saffron crocus (1). The resulting dried "threads" are distinguished by their bitter taste, hay-like fragrance, and slight metallic notes.

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Saffron is native to Southwest Asia but was first cultivated in Greece (6). Iran, Spain, India, Azerbaijan, Morocco, and Italy dominate the world saffron harvest; with Iran alone producing more than 65% of the world crop (16).

Both harvest and post harvest processing of saffron require intensive hand labor operations, particularly for flower picking and stigma separation. Flower picking in the field constitutes almost one third of the total production costs.

Increasing labor costs have turned production unprofitable despite its high market price (18). The high cost of saffron is due to the difficulty of manually extracting large numbers of minute stigmas. Nowadays, almost all saffron manipulations are carried out manually, however, machines for saffron bulb planting have been developed (14). To make saffron production profitable, the most labor-requiring steps should be mechanized (15).

The first and most important step to design an automated system to harvest saffron flower is developing a suitable algorithm to recognize and allocate the flowers in the field. This algorithm must separate the flower from other objects such as soil, saffron leaves, weeds, and brush woods. The considerable difference between the colors of the aforementioned objects encourages the use of color descriptors to discriminate the flowers.

As the second phase of saffron production, post harvest processing is another challenge. A vision based system was used 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 (9).

Robotic harvesting is being developed for several agricultural products. Machine vision serves as the main detection system in most harvesting robots. Bulanon et al. (2), for example, developed an algorithm for the automatic recognition of Fuji apples on the tree, which recognized the fruit from other objects in the image using the red color difference.

Huang and Lee (12) also developed a vision-guided grasping system for Phalaenopsis tissue culture plantlets. They employed an image processing algorithm to determine the suitable grasping point on plant roots.

Similarly, Hemming and Rath (10) used digital image analysis to develop an identification system for weeds in the crops. Their experiments showed that color features were successful for the segmentation procedure of plants from soil.

Chien and Lin (4) 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.

In the same line, automatic identification of plant disease visual symptoms was achieved using an image-processing based algorithm developed by Camargo et al. (3).

A neural network is a nonparametric calculative approach that correlates input data to the desired outputs by special learning processes. High processing speed and the ability to remove the effect of noises are two important specifications of artificial neural networks. Recently, machine vision systems combined with artificial neural networks (ANN) have been widely used to improve conventional modeling techniques (19). The application of image based neural networks is commonly found in various agricultural and post-harvest activities such as sorters and classifiers (17), yield prediction (7, 13), weed recognition and discrimination (5, 21) and forecasting the maturity of agricultural products (11). Nonparametric feed-forward ANNs quickly turned out to be attractive trainable machines for feature-based segmentation and object recognition (8).

Research on automatic saffron harvesting is scarce. The objectives of this study, are therefore, to develop a recognition and locating algorithm for a machine vision based system to be used in a saffron harvesting robot. The harvester is programmed to autonomously recognize and locate the flowers and direct the vacuum snapper (the picking device). Since various lighting conditions appearing in the field can affect color components, the algorithm must be programmed to be invariant to light and shadow. An evaluation of the ANN classifiers used to enhance the recognition results is another aim of the present study.

MATERIALS AND METHODS

Image Acquisition

Istahban in the Fars province, Iran, is one of the most important regions for saffron production. Several digital images were captured from Istahban saffron fields by means of a CCD camera (Canon IXUS 960IS; 12 megapixel with 3.7x optical zoom lens), mounted vertically at the distance of 30 cm above the flowers on a chassis to keep the distance identical for all flower samples. Saffron flowers were selected randomly. RGB images were taken under natural daylight conditions (sunlight, shaded and cloudy conditions), transferred to the computer and analyzed using image processing toolbox version 6.00 for MATLAB version7. Twenty images were used for the image analysis and 50 images were used to assess the algorithm.

Image Segmentation Algorithm

Due to the distinct colors of saffron flowers and other objects in the images, color features of the images were used for analyses. To eliminate the effects of light and shadows in the images, HSI and YCrCb color spaces were studied.

In the first algorithm, RGB images were converted to HSI color space whose three components are: hue (H) perceived as color, saturation (S) and intensity (I).

Intensity is sometimes substituted with brightness and known as HSB. The HSI color space closely approximates the behavior of the human eye. The segmentation algorithm based on Hue components of HSI color space is shown in Fig 1. The same procedure was performed on saturation components in HSI mode.

In HSI color space, it is possible to separate color from brightness, making it a suitable space to exclude lighting effects from the color of objects. The RGB to HSI conversion is defined by the following equations (22):

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

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

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

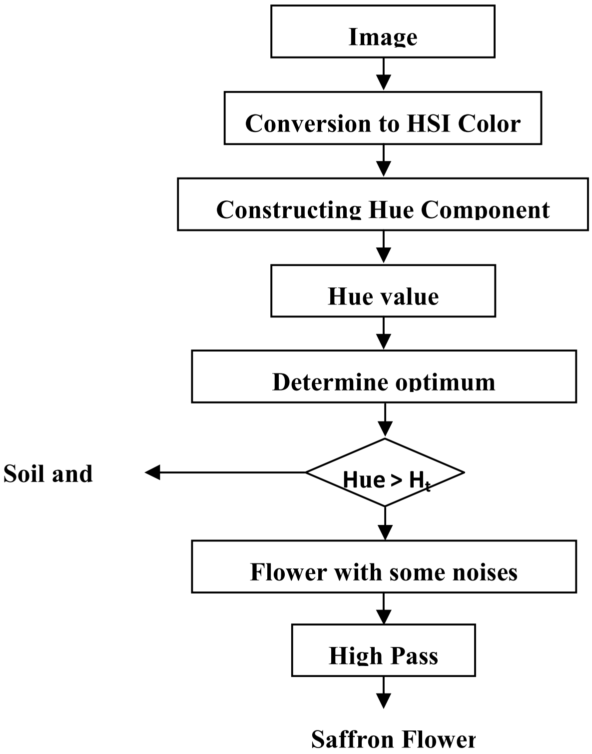

Fig. 1. Flower segmentation algorithm based on Hue

where the H, S and I components range from 0 to 1. To segment the flowers from soil and residues, a hue histogram was drawn (Fig. 2.a). Optimum threshold value (H_t) was determined based on the histogram valley of the corresponding component which is the lowest point between the two distributions.

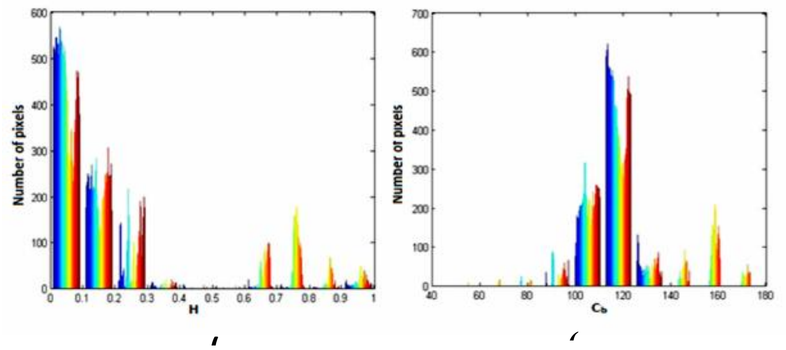

Fig. 2. a) Hue component histogram b) C_b component histogram

In the second segmentation algorithm, luminance (Y) and blue color difference (C_b) of YC_rC_b space were used (Fig. 3). The following equations convert RGB space to YC_rC_b space (2):

$$Y = 0.3R + 0.6G + 0.1B \quad (4)$$
$$C_r = R - Y \quad (5)$$
$$C_g = G - Y \quad (6)$$
$$C_b = B - Y \ , \quad (7)$$

where R, G and B are red, green and blue color intensity values ranging from 0 to 255. Fig. 2.b represents the distribution of the blue difference component for flowers and the background. Primitive tests showed that red and green color differences (C_r and C_g) were not practical criteria to segment the flower from the background and did not lead to useful results in this case.

Each of the main components of the RGB image increase when ambient luminance increases. Since the sum of the coefficients of R, G and B values in Cb equation (Eq. 7) is zero, the blue chrominance value (Cb) would be insensitive to this luminance increase, meaning that the situation of the flower in light or shadow does not affect the segmentation result.

$$C_b = B - Y = 0.9B - 0.3R - 0.6G = 0.9(B+M) - 0.3(R+M) - 0.6(G+M) \quad (8)$$

where M is an increase in RGB color components due to ambient luminance increment.

In both algorithms, some noise remains after conversion to binary images using thresholds. To remove this noise, high pass filters and morphological operations were applied to the images. Accordingly, no background pixel was left in the binary images.

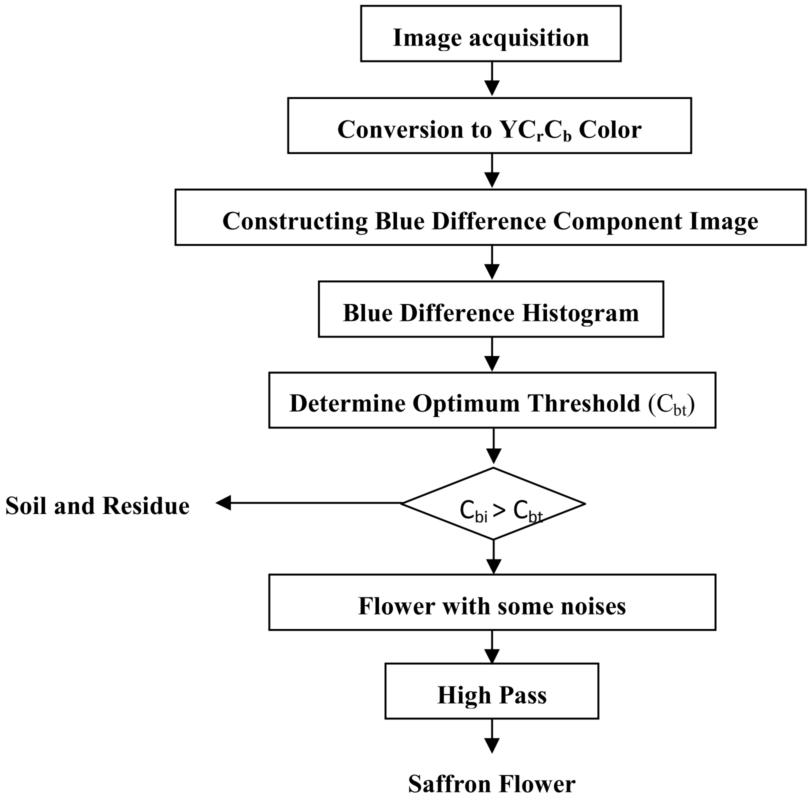

Fig. 3. Flower segmentation algorithm based on blue difference component

In cases where saffron flowers overlapped, sequential erosion and dilation operations were performed on the images to isolate the flowers, which were then labeled. Finally, the center area for each labeled object was determined as the location of the saffron flower in the image. The algorithms were evaluated by measuring the percentage of the correct segmentation rate (CSR) of the pixels. The CSR was defined as the ratio of flower pixels correctly segmented as flower to the number of flower pixels. An incorrect segmentation rate (ISR) was defined as the ratio of flower pixels misclassified as other objects to the total number of flower pixels.

Artificial Neural Networks (ANN)

ANNs were exploited to detect and segment the flowers from leaves, soil and residues using the aforementioned HSI and YCrCb components. Feed-forward multi-layer perceptron (MLP) networks with two hidden layers were used for classification. Levenberg-Marquardt back propagation learning algorithm and hyperbolic tangent sigmoid transfer function were configured in the networks. RGB color components were used as input data for the network as well as HSI and YCrCb color components in other networks. Output data comprised of flower, leaves and soil. The best network was selected regarding two statistical parameters; a correlation coefficient (r) and a root mean square error (RMSE), defined as Eq. of 9 and 10, respectively. RMSE is one of the most commonly used statistical parameters, which represents the average difference between estimated and observed values (20).

$$R = \left[1 - \frac{\sum_{i=1}^{N} (Y_{\exp,i} - Y_{ANN,i})}{\sum_{i=1}^{N} (Y_{ANN,i})} \right] \times 100 \tag{9}$$

$$RMSE = \left[\frac{1}{N} \sum_{i=`}^{N} (Y_{ANN,i} - Y_{\exp,i})^2 \right]^{1/2} , \tag{10}$$

where N is the number of pixels or color components applied in the ANN, $Y_{\exp,i}$ is the group the *i*th pixel belongs to, and $Y_{ANN,i}$ is the output of ANN for *i*th pixel.

RESULTS AND DISCUSSION

HSI and YC$_r$C$_b$ potentials in segmentation

It might be desirable to know whether it were possible to segment objects using main RGB color components. Therefore, a comparison was made between the scatter plots of the RGB color components of flowers, leaves, soil and residues. Fig. 4 illustrates the distribution of these components in RGB space. It is clearly seen that a heavy occlusion of RGB color components exists among the aforementioned groups, making it impossible to separate the groups completely.

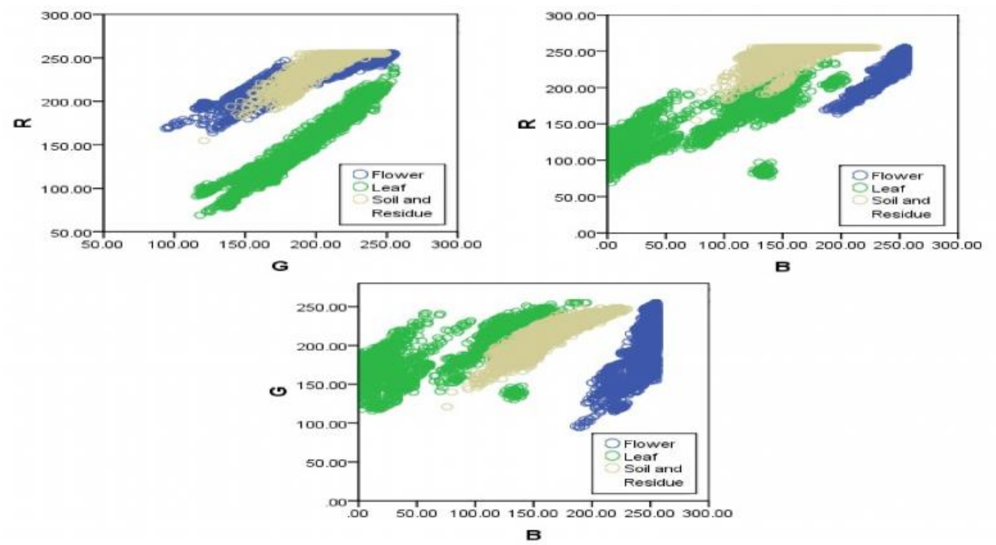

Fig. 4. Scatter plots of RGB color components of flowers, leaves, soil and residues

Comparison was made between each HSI and YCrCb component corresponding to the pixel values of saffron flowers, leaves, soil and residues to select the best color components providing optimum segmentation. Those color components with the most significant differences between flowers and other objects were selected. T-tests were carried out to compare the means. Results are shown in Table 1.

Table 1. Objects discrimination based on $C_rC_gC_b$ and HSI components using t-test

Color Component		*Saffron flower*	*Soil and residues*	*Green leaves*
	Saffron flower	--------	**	**Ns**
C_r	**Soil and residues**	**	--------	**
	Green leaves	**ns**	**	--------
	Saffron flower	--------	**ns**	**
Cg	**Soil and residues**	**ns**	--------	**
	Green leaves	**	**	--------
	Saffron flower	--------	**	**
Cb	**Soil and residues**	**	--------	**Ns**
	Green leaves	**	**ns**	--------
	Saffron flower	--------	**	**
H	**Soil and residues**	**	--------	**
	Green leaves	**	**	--------
	Saffron flower	--------	**ns**	**ns**
S	**Soil and residues**	**ns**	--------	**ns**
	Green leaves	**ns**	**ns**	--------
	Saffron flower	--------	**ns**	**ns**
I	**Soil and residues**	**ns**	--------	**ns**
	Green leaves	**ns**	**ns**	--------

ns: Corresponding to no significant difference. **: Corresponding to 1% probability.

Evident differences between saffron flowers and other objects were seen between the Hue component in HSI space and the C_b component in YC_rC_b space, while in case of the other components it was almost impossible to find an appropriate boundary to recognize flowers in the images. This means that the flower group overlapped the leaf and soil groups when C_r and C_b components were used separately.
An interesting finding is that for the hue component, the only significant difference was found in HSI space, while it might be expected that flowers are more saturated in color than soil and leaves. It is obvious that the intensity component was not able to differentiate the groups because it reflected the illumination and brightness of the objects irrelevant to the object categories.

Duad consideration of color components has the preference to visualize the groups' spatial distribution to determine the separating line. It can be seen in Fig.5 that the flowers showed the most significant difference with leaves, soil and other residues when C_b and H color components are used. Therefore, these two components were used in the segmentation algorithms.

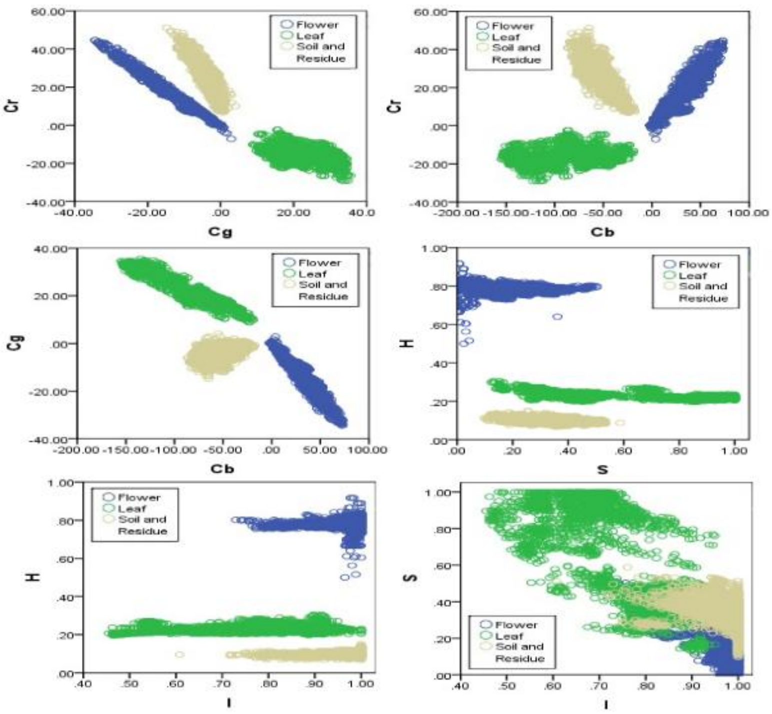

Fig. 5. Scatter plots of HSI and YC_rC_b color components for flower, leaves, soil and residues

A significant difference was also found between leaves and other objects in the C_g component, which can be used to discriminate the whole plant from the soil.

From Fig 5, the reason why the segmentation of flowers from leaves and soil was not possible when color components C_r and C_g were used separately could be understood. Comparing the one color component segmentation results (Table1) with the duad consideration of color components (Fig. 5), it can be concluded that segmentation is also possible if a separation line comprising two color components C_r and C_g separates the groups.

It is also true for other cases that segmentation would be enhanced if a combination of two components was used in the analysis.

Table 2 shows the correct segmentation rate (CSR) of the two different procedures. The CSR for HSI method was 96.4% while this accuracy rate was 98.7% for the YCrCb method. Results showed that the thresholds used to segment images under different lighting conditions were the same, because the algorithm used an H color value in HSI color space and a C_b value that removed the effect of brightness in images. This indicates that the algorithm is not dependent on the conditions the images were taken and can be useful in different daylight conditions. The gallery of image segmentation steps is illustrated in Fig. 6.

Table 2. Segmentation results of the HSI and YC_rC_b methods

			Soil and residue	*Green leaves*	*Saffron flower*
Method	H	Soil and residue	97.1	1.8	1.1
		Green leaves	1.3	98.3	0.4
		Saffron flower	2.0	1.6	96.4
	C_b	Soil and residue	97.4	1.6	1.0
		Green leaves	1.5	98.1	0.4
		Saffron flower	0.6	0.7	98.7

ANN results

Extending the duad consideration of color components to a 3-D combination of the features leads to more effective separation of the groups. Such consideration is possible when artificial neural networks (ANNs) are used.

In this stage, all effective components from the last experiments were used as input for the ANN. The performance of each ANN is illustrated in Fig. 7 by plotting the simulated against the observed data. Best results were obtained when Cr, Cg and Cb color values were used to classify saffron flowers from leaves, soil and residues. This network resulted in the highest R (= 99.93%) and lowest RMSE (=0.00973). The value of RMSE can be considered to be fairly close to zero which indicates that on average, there is no difference between the simulated and observed data. The values of R and RMSE were 99.76% and 0.01205 obtained when HSI color components were used as ANN input and 67.39% and 0.08472 in the case of RGB color space. These results imply the accuracy of the ANN method in improving the capability of machine vision to distinguish saffron flowers from other objects.

Flower Locating

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. Thus, a special spot must be defined for the robot as the location of the flower. The centroid (center of the area) of the flower was considered as an estimate for the location of the peduncle.

Peduncle detection error (PDE) was defined as the difference between the positions of the flower centroid with respect to the peduncle. PDE was determined using Eq. 11.

$$PDE = \sqrt{(X_c - X_a)^2 + (Y_c - Y_a)^2} \ , \qquad (11)$$

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

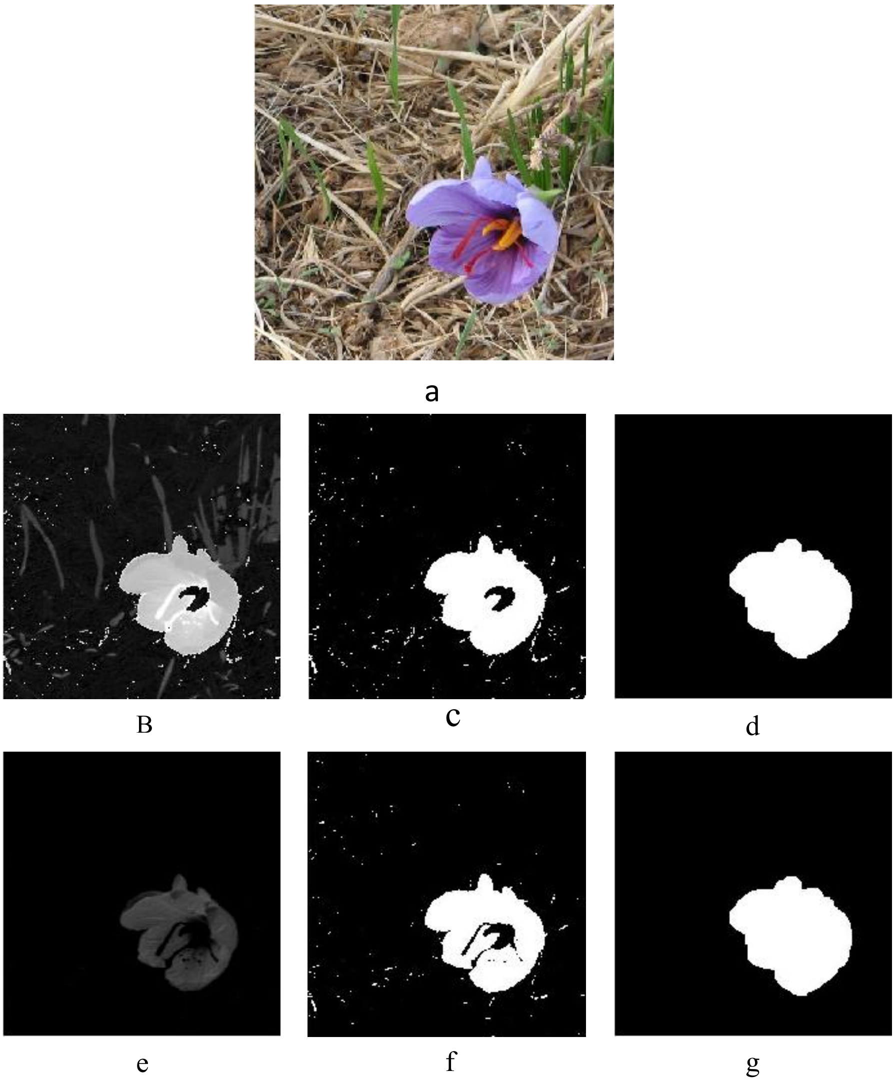

Fig. 6. Example of saffron flower recognition using two different method: (a) original color image of saffron; (b) Hue component image; (c) binary image using Hue value threshold; (d) final segmented image after noise removal and morphological operations; (e) Blue color difference C_b component of the image; (f) binary image using threshold on blue color difference; (g) final segmented image using blue color difference method.

The negligible difference between the methods can be referred to different detected areas caused by differences between the CSR of the methods. Nevertheless, the main source of variation in PDE in both methods was due to the inclination of flowers with respect to the imaging direction.

It was observed that when images were taken perpendicular to the flower, PDE error diminished even to zero, an important point recommended for future consideration.

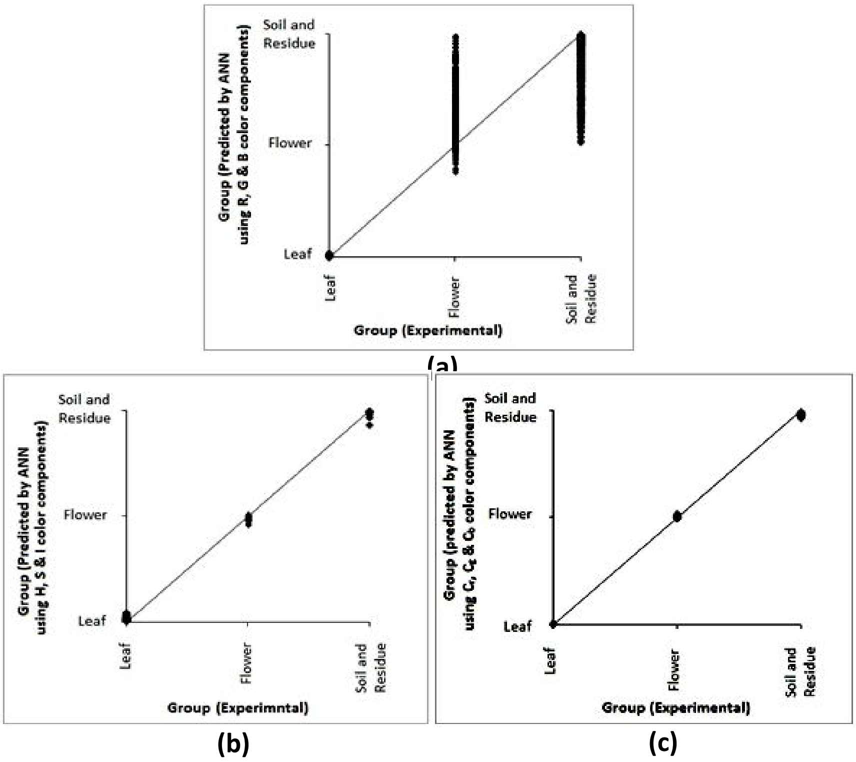

Fig. 7. Performance of the ANNs for classification of saffron flowers from leaf, soil and residues; a) RGB color space, b) HSI color space and c) YCrCb color space

Table 3. Results of PDE for Hue and blue color differences

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

CONCLUSIONS

Two different algorithms for saffron flower detection were developed based on hue (H) and blue color difference (C_b) components of the images. The accuracy of the methods was verified while Cb component yielded better detection results.

The duad consideration of color components enhanced the segmentation results, while ANNs made it possible to achieve segmentation based on 3D color components. It can therefore, be concluded that segmentation using ANNs are more robust to changes in the situations and data loss. This is one of the well known characteristics of ANNs which is their potential for parallel considerations of several inputs.

In the next step, the position of the flower was addressed based on its centroid. Results showed that when images were taken perpendicularly to the flower, the centroid could be considered as a good reference for further use by the harvesting machine. For more accurate positioning of the peduncle or stigma, the addition of more equipment is recommended to comb and straight up the flowers. The combination of neural networks and image processing techniques helped recognize saffron flowers with an accuracy of almost 100%.

The results clearly indicate that the methods used in this study can be potentially used to recognize and locate flowers in the field, which could be a first step towards designing an automated saffron harvester.

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چکیده- برداشت دستی زعفران یک کار دشوار و خسته کننده نه تنها موجب افزایش هزینه‌های تولید می گردد بلکه در اثر آلودگی، موجب کاهش کیفیت آن نیز می‌شود. درصورتی که برداشت خودکار زعفران جایگزین روش کنونی شود کیفیت زعفران ارتقاء خواهد یافت. در این تحقیق، به عنوان اولین مرحله از طراحی یک روبات برداشت زعفران، الگوریتم مناسبی برای تشخیص و مکان یابی گلهای زعفران بر اساس پردازش تصاویر در مزرعه ارائه شد. از ویژگی های رنگی تصاویر در فضاهای رنگی RGB، HSI و YC_rC_b به منظور تشخیص گلها استفاده گردید. برای حذف نوفه‌های تصاویر جداسازی شده، از فیلترهای بالاگذر استفاده شد. انسداد جزئی گلها با عملیات سایش و گسترش اصلاح شد. سپس گلهای جداشده علامتگذاری شدند. چنین در نظر گرفته شد که ماشین برداشت گل پیشنهاد شده با یک ربانیده مکشی اقدام به چیدن گلها نماید. بنابراین مرکز سطح گل، بعنوان موقعیت گیاه که می‌بایست توسط ماشین برداشت تشخیص داده شود توسط الگوریتم محاسبه گردید. تشخیص صحیح الگوریتم با تصاویر طبیعی شامل زعفران، برگهای سبز، علف های هرز و خاک زمینه، اندازه‌گیری شد. دقت تشخیص الگوریتم در مکان یابی گلها هنگامی که فضای HSI **و** YC_rC_b مورد استفاده قرار گرفتند، به ترتیب برابر ۹۶/۴ ٪ و ۹۸/۷٪ بود. زیرروال های نهایی تصمیم‌گیری از شبکه‌های عصبی مصنوعی استفاده می‌کند تا دقت تشخیص را افزایش دهد. هنگامی که شبکه های عصبی به کار گرفته شدند نرخ تشخیص صحیح ۱۰۰٪ به دست آمد.

واژه های کلیدی: زعفران، شبکه‌های عصبی مصنوعی، ماشین برداشت، ماشین بینایی

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