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Recognition and localization of ripen tomato based on machine vision

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Abstract

Fruits picking by human is a time consuming, tedious and expensive task. For this reason, the automation of fruit harvesting has achieved great popularity in the last decade. Tomato fruits do not ripe simultaneously and one of the main challenges in the design of a tomato harvester robot is its ability in recognition and localization of ripen tomato on the plant. In the current study, a new segmentation algorithm was developed for guidance of a robot arm to pick the ripen tomato using a machine vision system. To reach this aim, a vision system was used to acquire images from tomato plant. The recognition algorithm had to be adaptive to the lighting conditions of greenhouse. Totally 110 color images of tomato were acquired under greenhouse light conditions. The developed algorithm works in two steps: (1) by removing the background in RGB color space and then extract the ripen tomato using combination of RGB, HSI, and YIQ spaces and (2) localizing the ripen tomato using morphological features of image. According to the results, the total accuracy of proposed algorithm was 96.36%.

Keywords: localization, machine vision, recognition, robot, tomato, watershed.
Abbreviations: 3CCD; 3 Charged Coupled Device; RGB- Red, Green, Blue; HIS- Hue, Saturation, Intensity; RT- Ripen Tomato; UT- Unripe Tomato; OR- Opening by Reconstruction.

Introduction

Tomato is grown worldwide for its edible fruits which has many vitamins and beneficial nutrients. Thousands of cultivars have been selected with different fruit types, and for optimum growth in various growing conditions (Moneruzzaman et al., 2009). Since export of tomato fruit and it's lateral products, like ketchup and tomato sauce, have considerable income for Iran, its cultivation increased greatly in the last years (Gheshm and Kafiee, 2006). The greenhouses can be constructed everywhere and used to produce tomato in all seasons of year. Moreover, high labor cost has been the main obstacle in expansion of greenhouses. According to the Sarig, (2005) cost of harvesting by labors is very expensive and time-consuming. In addition, picking of fruits by hand is very tedious. To solve these problems, human works can be replaced by automatic robots. Automatic harvest operations reduce the harvesting costs. Therefore, automation and use of image processing methods in agriculture have become a major issue in recent years (Wang et al., 2008; Vesali et al., 2011; Ahmad et al., 2010). The first major task of a harvesting robot is to recognize and localize the fruit on the tree or plant. Recognition is the process of separating an object of interest from the background. This is an image processing procedure called segmentation (Bulanon et al., 2002). Several studies have been carried out to design a harvesting robot to pick up fruits from the trees or plants (Hayashi et al., 2005; Chinchuluun et al., 2006; Bulanon et al., 2004; Plebe and Grasso, 2001; Edan et al., 2000). In the most cases, navigation of robot was carried out using a machine vision based system. Wang et al., (2008) used RGB model for recognition of cotton. They used the R-B feature for this purpose. Hanan et al. (2009) developed a vision system to pick orange using a harvesting robot. The R/(R+G+B) feature was used for recognition of orange fruits on the tree. An algorithm for the automatic recognition of Fuji apples on the tree was developed for a robotic harvesting system by Bulanon et al. (2002). Since the color of Fuji apple was red, difference between luminance and red color (R-Y) was only used. In the case of tomato fruit, some studies have been carried out to find an appropriate image processing algorithm for sorting or automatic harvesting purposes (Choi et al., 1995; Laykin et al., 2002; Hayashi et al., 2005;). Tomato is a plant that its products do not ripe simultaneously. On each tomato plant, green, yellow, orange, and red tomatoes can be found. Therefore, the harvesting robot must have the ability to detect all of these types of tomato colors and pick up only the ripen ones. Because color range of UT and RT is close together and color of RT is not uniform (There is yellow- red color pixels in a RT), no appropriate algorithm has been reported yet to detect the RT on the plant. Hence, the object of this study was to introduce and develop a new algorithm for recognition and localization of RT from the background (green, branches, leaves and greenhouse space) and UT (yellow and orange tomato) based on the color quantification and shape of fruit.

Results and Discussion

Lighting condition of greenhouse was not uniform during the image acquisition. The RGB color model could not lonely be used to recognize RT, because of high correlation among the R, G, and B components (Pietikainen, 1996; Littmann and Ritter, 1997). In the cases that UTs were under poor lighting

Table 1. The confusion matrix shows number of correct and incorrect objects that were recognized by proposed algorithm.

Output/Desired	RT	UT	Background
RT	105	7	0
UT	5	103	0
Background	0	0	110

Table 2. The values of recognition accuracy criteria were obtained by proposed algorithm.

Objects	Statistical parameter		
	Sensitivity (%)	Specificity (%)	Total accuracy
RT	95.45	97.72	
UT	93.63	96.81	96.36
Background	100	100	

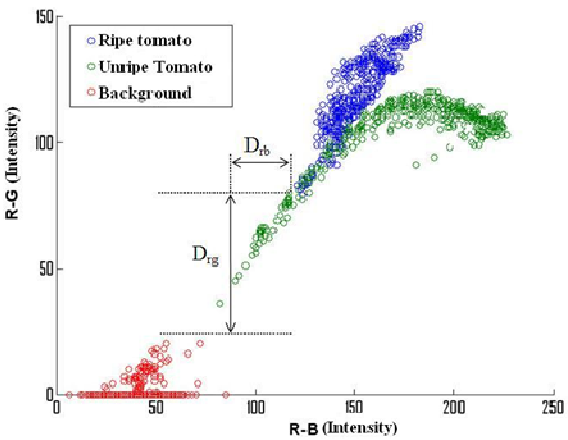

Fig 1. Pixel distribution diagram of the RT, UT, and background.

conditions, it looked darker and the RGB color model wrongly detected them as RT. The HSI and YIQ color models were successfully able to solve this problem. Because in the HIS and YIQ color models intensity information of an object is separated from the color information (Robinson, 1977; Cheng et al., 2000; Katsumata and Matsuyama, 2005).

Removing the background

The D_{rg} equation could produce a high contrast image between tomatoes and background. This is one of the most successful agents in image segmentation based on the threshold values (Zheng and Sun, 2008). Although obtained result by D_{rb} equation was acceptable, but comparison between D_{rg} and D_{rb} equations showed that difference between pixel values of tomato and background for D_{rg} was more than that for D_{rb} (Fig 1). Finally, it was concluded that D_{rg} equation can be appropriately used to remove the background. Figure 5 shows an image sample and its histogram corresponding to the D_{rg}. In the image histogram, the RT with more R-G value is placed in the right side and background is placed in the other side. Sometimes because of progressive ripening the top parts of RTs have green color. Therefore, with removing the background the upper parts of RTs will be removed as well. To solve this problem, it is necessary that images be taken in the side view. It should be mentioned that in some greenhouses a string is used to hold tomato plants upward. In the cases that the color of strings is red, they will be recognized as tomato fruits. To solve this problem, it is suggested that strings with red color must not be used.

Detection of RT

Using Eq. 1 and Eq. 2, UTs were successfully removed and the RTs were extracted. The HSI and YIQ color systems algorithm were able to overcome the non-uniform lighting condition of greenhouse led to increase the accuracy of RT extraction. Table 1 shows the confusion matrix of images, which were used to test the algorithm. The diagonal elements in the confusion matrix showed the number of correctly recognized objects. In the first column, the first element indicates the number of images belong to the RT and recognized by algorithm as RT. The second element shows the number of images belonging to RT but misrecognized the UT and etc. Sensitivity, specificity, and total classification accuracy were three statistical criteria, which were used to determine the test performance of algorithm (Mollazade et al., 2009). According to the values of statistical parameters (Table 2), the algorithm showed this potential to completely recognize the background from the other objects and high recognition rate was observed for RT (95.45% sensitivity) and UT (93.63% sensitivity) as well. Moreover, the total

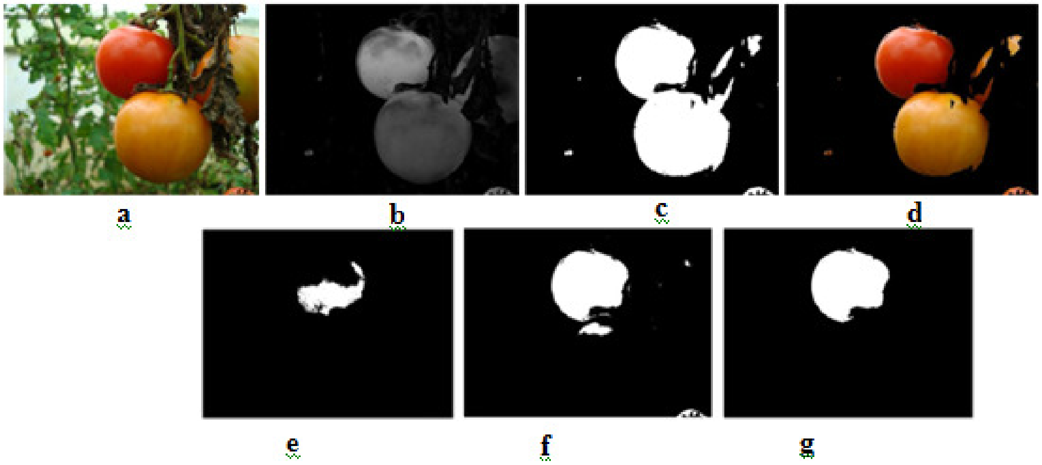

Fig 2. Typical RT recognition. (a) Original color image (b) Gray image (c) Binary image (d) Image after removing the background (e) Extraction of red pixels by Eq. 1, f. Result of Eq.2, and g. RT recognition.

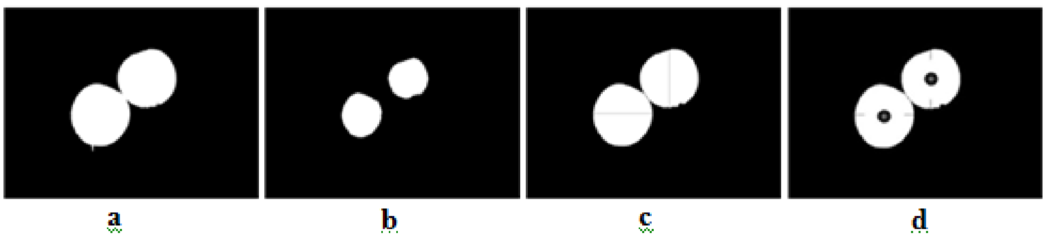

Fig 3. Typical RT localization. (a) Two glued RT (b) Result of erosion operation (c) Separated tomato by watershed algorithm (d) Localization of tomato (Centre of area is shown by * sign).

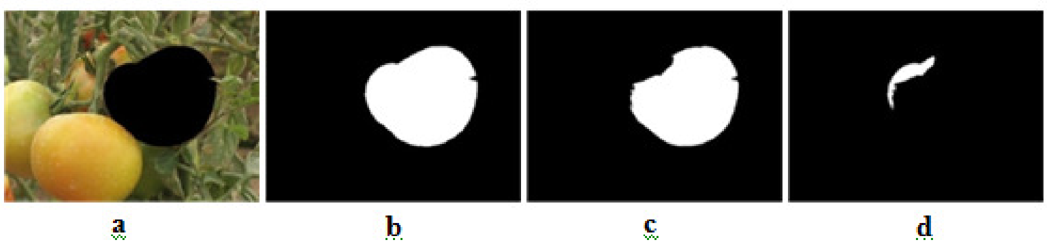

Fig 4. Test of algorithm using comparison between detected area of original and manually marked images of RTs. (a) Manually marked test image (b) Reference image (c) Result of algorithm (d) difference between b and c.

recognition accuracy of algorithm was obtained to be 96.36%. Those parts of the RT, in which their light reflection was high, were not extracted with the RT. The color of these parts in the acquired images was similar to white and the difference between R and G components was equal to zero. The similar problem was reported by other researches on fruit harvesting robotics (Hayashi et al., 2002; Bulanon et al., 2004; Gu et al., 2006). Full area extraction of RT is an important factor in an image to design the harvesting robot. Fig 6. shows the comparison between ideal and extracted area using proposed algorithm. According to the results, the average of error between ideal ripen area and estimated ripen area for 40 images was about 7%. The proposed algorithm was able to analyze an image and extract the RTs in 2.2 s. This processing time is suitable for harvesting systems, but this time can be reduced using stronger hardware implements for rapid applications (Van Henten et al., 2002; Van Henten et al., 2003; Tanigaki et al., 2008).

Localization of RT

The watershed algorithm could successfully separate glued tomatoes. Although over-split of an individual tomato was the main drawback of algorithm. To solve this problem, erosion operation was conducted. In some cases, tomato edge was segmented into several slices by watershed algorithm and therefore; the erosion operation was not able to rejoin the slices. Thus, these parts were wrongly localized as an individual object. The size of disk in the erosion operation was 45. This value was determined by analyzing of 90 images. This disk size showed acceptable results, but when the size of RTs was smaller than disk, algorithm did not show reliable result. In this case, tomatoes were wrongly removed by the erosion operation. Furthermore, when the number of glued tomatoes were higher than two (they make up a big tomato), the defined disk was not able to separate all of tomatoes. So, several tomatoes were localized as a one tomato. Overall, localization of tomato was carried out with

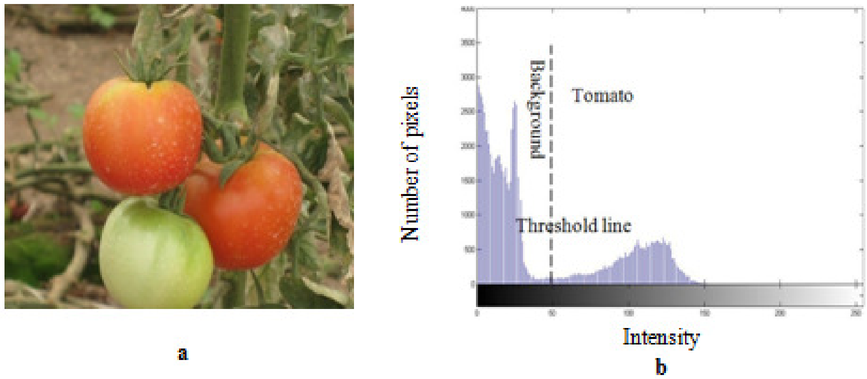

Fig 5. The corresponding Histogram to D_{rg} relation. (a) original image (b) corresponding histogram.

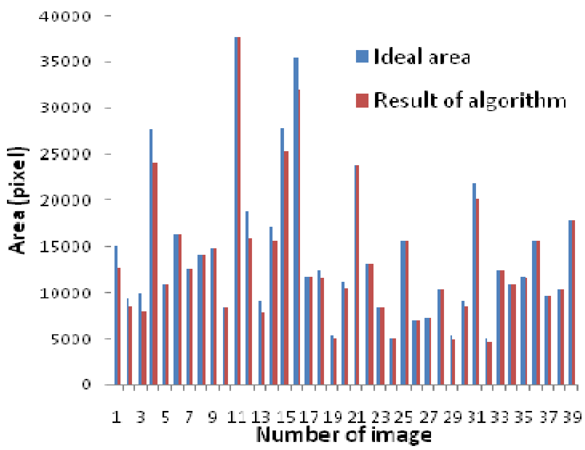

Fig 6. Comparison between ideal area and area extracted with proposed algorithm.

acceptable accuracy and the algorithm was truly able to localize the 82 from 90 tomatoes in the testing images. The accuracy of algorithm was 91.11%.

Materials and methods

Image acquisition

Using a 3CCD camera (Sony Cyber Shot w200, Japan) 110 tomato images of greenhouse-grown variety was acquired in the RGB color model. Camera was placed in facing of plant rows and in 20 cm distance from the tomato plant. The natural conditions of greenhouse were selected for taking the images and no extra lighting system was used. The resolution of taken images was 1944×2592 pixels.

Hardware and software

A personal computer with 2.20 GHz processor and 1.00GB RAM was used as hardware part of machine vision system and algorithm was developed in MATLAB R2007 version software.

Preprocessing operations

The processing time depends on the size of images. The higher the image size, the longer the processing time. Since, the size of taken images was large and their processing time was long, size of images was reduced to half.

Segmentation

Segmentation is one of the most important and difficult tasks in image processing. Segmentation subdivides an image into its items. When interested object in an application was extracted, segmentation should be stopped (Gonzalez and Woods, 2002). The aim of segmentation process in this study was to recognize the RT from the background. This process has been performed in tow separate steps as described in the following subsections.

Removing the background

As mentioned previously, background includes green tomato, branches, leaves and greenhouse space. For removing the background several steps were carried out as follows:

1) The color data of objects such as background, RT, and UT were extracted in RGB color model. D_{rg} =R-G and D_{rb}= R-B were the equations that defined for removing the background. Fig 1. shows the pixel distribution diagram of the objects. It can be observed that the RT has the highest R-G value in comparison with the other objects. Hence, the R-G was applied as the threshold parameter (threshold value was

automatically obtained by image processing toolbox of Matlab). A typical image and result of D_{rg} are shown in Fig 2-a and b, respectively.

2) The gray image obtained from D_{rg} was converted to binary image. It should be mentioned that RT and UT had 1 value and background had zero value (Fig 2-c).

3) To remove the background, the binary image was multiplied in R, G, and B channels separately.

4) The color image was reconstructed by composition of R, G, and B channels obtained from the previous step (Fig 2-d).

Recognition of RT

RT recognition was carried out using color features in two steps as described in the following:

1) Comparison of extracted color data from the UT and RT showed this fact that red pixels only exist in the RT. The location of these pixels was in the bottom part of RT, because tomato fruit would start to grow from the bottom to the top parts. These pixels could be used for recognition of RT. The RGB components change when the intensity changes. So, images were first transformed to YIQ color model. The YIQ color model can partly neutralize the correlation of the red, green, and blue components in an image (Cheng et al., 2000). To extract these pixels from the whole tomato, Eq. 1 was defined in YIQ color model. This color model obtained from RGB color model by following linear transformation (Cheng et al., 2000).

$$\begin{bmatrix} \mathrm{Y} \\ \mathrm{I} \\ \mathrm{Q} \end{bmatrix} = \begin{bmatrix} 0.299 & 0.587 & 0.114 \\ 0.596 & -0.274 & -0.322 \\ 0.211 & -0.253 & -0.312 \end{bmatrix} \times \begin{bmatrix} R \\ G \\ B \end{bmatrix}$$

Luminance (Y), hue (I) and saturation (Q) are three components of this model. Result of Eq. 1 is shown in Fig 2-e.

$$\mathrm{Y} - \mathrm{I} < 0.01 \quad \& \quad \mathrm{Q} > 0.08 \qquad (1)$$

2) Images were transformed from RGB to HSI color model and then to reduce the effect of reflected light on the RT; the saturation value of all pixels was placed equal to each other. The HSI system is another color space in image processing, which is more intuitive to human vision. Hue, Saturation and intensity are three component of HSI color model that defined as bellow:

$$H = \arctan\left(\frac{\sqrt{3}\times(G-B)}{(R-G)\times(R-B)}\right)$$

$$S = 1 - \frac{\min(R,G,B)}{I}$$

$$I = \frac{R+G+B}{3}$$

To extract the RT, Eq. 2 was defined in RGB and HSI color spaces. Fig 2-f shows the Result of Eq. 2.

$$\mathrm{P} = 0.25\times \mathrm{G} - \mathrm{H} \qquad (2)$$

Result of Eq.2 is including both the completely extracted RT and partial sections of UT. The UTs that are extracted with RT in step 2 should be removed. For this purpose, reconstruct function was used. This function has two inputs: the obtained results from the step 1 and step 2. Output of reconstruct function was based on the obtained result of step 1. Only, those tomatoes were recognized as ripen that their pixels were extracted in the step 1 (Fig 2-g).

Removing of noise

Tomato plants in greenhouse are cultivated in rows, so tomatoes which belong to the behind rows may be extracted with those in interested row. It was necessary to eliminate RTs which are not belonging to the interested row; otherwise robot would act to pick them mistakenly. RTs of rows look smaller than those of interested row, so the algorithm was developed to remove the extracted tomatoes as a noise when their size was smaller than a certain value. To reach this aim, OR operation was used (Gonzalez and Woods, 2002).

Localization of tomato

Localization of fruit is another key task in robotic application. In this study, first connected objects in a binary image were computed by labelling function. Then the row and column indices were found for all of the pixels belong to each connected component. Finally, mean value of found row and column indices was computed as centre of area of each connected component (Gonzalez and Woods, 2002). In some cases, the RTs are glued together. This leads to multiple RTs be detected as a one big fruit (Fig 3-a). To overcome this problem, watershed algorithm was applied (Gonzalez and woods, 2002). This algorithm is able to separate the joined objects into individual ones. But, watershed algorithm split an individual tomato into several slices (Fig 3-c). To solve this problem, the binary image was first eroded using a defined global disk (Fig 3-b). Then watershed segmentation was applied to the binary image and finally, result of erosion was used to join over-segmented components (Fig 3-d).

Test of algorithm

To test the algorithm, 40 images were randomly selected. These images were transmitted to the Photoshop (adobe Photoshop 9.0 CS2) software and RTs were marked manually to create binary images. All of the 40 images were tested by algorithm and their results were compared to the references images (Fig 4).

Conclusion

In this paper a vision algorithm was designed to recognize the RT from the other objects of image as well as to determine their location. The algorithm was able to identify RT by high accuracy in different lighting conditions of greenhouse. Also, the algorithm showed reliable for robotic harvesting operations. About 93% area of a RT was extracted by proposed algorithm. This shows the suitability of algorithm to use in machine vision guidance based harvesting robots. The required time for processing of an image was 2.2 s. This low processing time makes the algorithm to be suitable for real time applications.

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