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A Machine Vision System for the Real-Time Harvesting of Ripe Tomato

Rahman FARROKHI TEIMOURLOU, Arman AREFI, Asad MODARRES MOTLAGH
Urmia University, Faculty of Agriculture, Department of Agricultural machinery, Nazlou, Urmia-IRAN
r.farrokhi@urmia.ac.ir

Abstract: Tomato fruit (Lycopersicon esculentum) is one of the most important produces in the world; therefore there is a high demand for greenhouse grown tomato. At the same time, the usage of automatic control methods in agricultural and greenhouse operations is increasing too, as part of the attempt to enhance efficiency and reduce labor costs. Thus, an algorithm was developed in this study for distinguishing the ripe from unripe tomatoes. For this purpose, 200 colour images of tomato in the natural conditions of greenhouse were acquired. Then colour data was extracted and an algorithm was developed using composite *RGB, HIS* and *YIQ* colour models, for recognizing the ripe tomatoes. The recognition process consists of two steps; i.e. removing of the background and distinguishing the ripe tomatoes. To simulate a realistic working environment, the algorithm was also tested under different lighting conditions of greenhouse. We found that the algorithm was able to extract 92-96% of ripe tomato area in an image. This encouraging level of precision provides the algorithm potential to be incorporated into an automated harvesting system.
Key words: Harvester, image processing, maturity, machine vision, measure, ripeness, tomato

INTRODUCTION

Tomatoes (Lycopersicon esculentum), with an annual production of 5 million tons, are one of the main horticultural crops in the Iran, with 130,000 hectares planted every year (Anonymous, 2009). Tomatoes are widely consumed either raw or after processing.

Since labour costs are high and ever rising, automated harvesting of fruits such as cucumber, paprika and tomato will be increasingly important in the near future. It is a feasible solution for farmers, especially those with greenhouses and it will become more important in concert with the growing number of greenhouse nowadays. This is one of the reasons why the use of an automated robotic system for harvesting is so attractive. The first major task of a harvesting robot is to recognize the fruit. There are several features that can be used for this purpose.

Colour is considered a good indicator of the quality of fresh-cut fruits and vegetables, including tomato. Traditionally, the surface colour of tomatoes is a major factor in determining the ripeness of tomato fruits (Arias et al., 2000) and consumer prefers bright red tomatoes over green or dark red tomatoes (Edan et al., 1997, Jahns et al., 2001). A more vivid red coloured tomato has more marketing values, because its flavor improves for table use as the tomato matures.

Maturity and ripening of tomatoes is a combination of processes, including the breakdown of chlorophyll and build-up of carotenes (Polder and Heijden, 2010). At different ripening stages, the colour of tomato varies from mature green, yellow, orange to intense red colour. Not only similarity between tomatoes makes it difficult to distinguish them, another major problem arises as different parts of tomato fruits do not ripe simultaneously. While the bottom part of tomato start ripening and became red, the other part can still be green, yellow and orange colour. Therefore it was necessary for a machine to pick only the ripe tomato and holds the unripe tomatoes for later.

The colour of object comes from the visible light that reflects at the object surface. Colour segmentation plays an important role in the area of quality control, image processing, pattern recognition, and computer vision. The visual appearance of food and other biological products is the foremost feature in the decision of quality, so visual inspection is the most important form of quality control in these aspects (Lin et al., 2011).

For automatic sorting of tomatoes, *RGB* colour cameras are used instead of the colour chart (Choi et al., 1995). *RGB*-based classification, however, strongly depends on recording conditions. Next to surface and reflection/absorption characteristics of the tomato itself, the light source (illumination intensity, direction, and spectral power distribution), the characteristics of the filters, the settings of the camera (e.g. aperture), and the viewing position, all influence the final *RGB* image. Arias et al. (2000) reported that the surface colour of tomato is a major factor in determining the ripeness of this fruit. Jahns et al. (2001) also reported that colour, spots and bruises are easily recognized by the pixel level. Hahn (2002) reported the application of a multi colour system to select tomatoes considered physiologically immature, claiming an approximation of 85%. Polder et al. (2003) reported that they found a good correlation between spectral images and the lycopene content of tomato that is responsible for the fruit's red colour, which varies according to the ripeness stage. Polder et al. (2004) developed the methods for measuring the spatial distribution of the concentration of these compounds in tomatoes using hyperspectral imaging. Schouten et al. (2007) also added firmness measurements to the tomato ripening model. They stated that, in practice, knowledge of the synchronization between colour and firmness might help growers to adapt their growing conditions to their greenhouse design so as to produce tomatoes with a predefined colour–firmness relationship. Lana et al. (2006) used *RGB* measurements to build a model in order to describe and simulate the behavior of the colour aspects of tomato slices as a function of the ripening stage and the applied storage temperature.

The disadvantage of spectrometer is that only a small number of points on an object are measured, which can give a misleading representation of the colour; as it mentioned previously that all parts of tomato do not ripe simultaneously. Spectral image yielded satisfactory result but the disadvantage is that the equipment involved is relatively expensive. In the limited research that used *RGB* image, it is not possible to extract the whole fruit.

The goal of this research was therefore to development an inexpensive method to distinguish the ripe tomatoes from the unripe ones, based on the normal camera and RGB image. The ability to find the whole tomato is an indispensable feature in designing the harvest robot.

MATERIALS and METHOD

The experimental setup was composed of a charged coupled device (CCD) camera (Sony Cyber Shot w200, resolution 1944×2592 pixels) and a personal computer with 2.20 GHz processor and 1.00GB RAM.

A total of 200 images of the tomatoes were taken as samples from greenhouses in natural condition and lighting. The distance of camera from tomatoes was about 20 cm.

A general process in image processing has been implemented in this project. It is consisted of three major stages as shown in Figure 1. Tomato maturity can be determined by its colour, and the colour of a mature tomato is defined as at least 90% red colour value of the whole tomato.

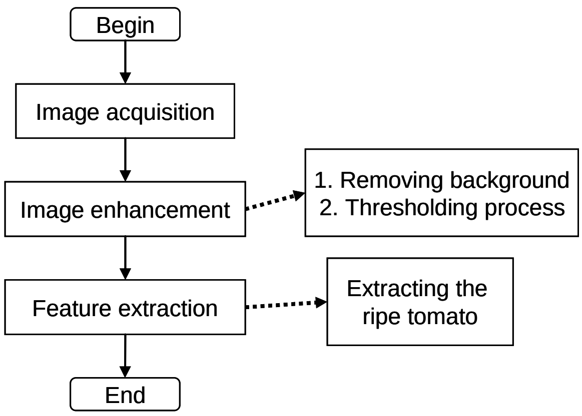
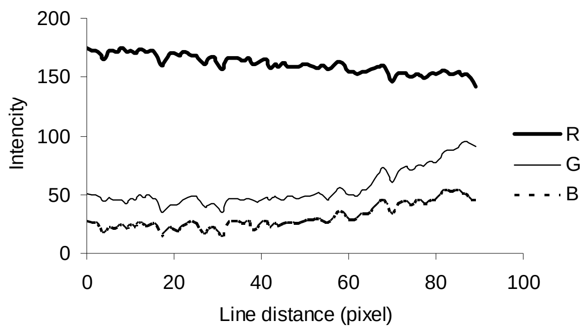
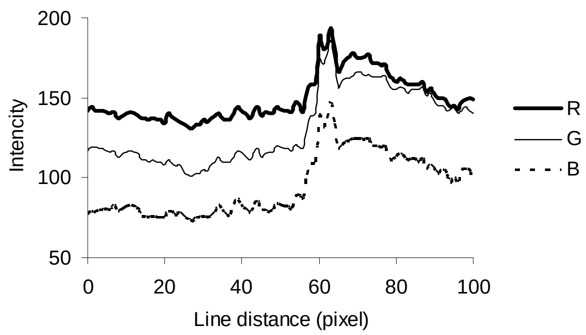


Figure 1. The flowchart of major image processing stages

At the first step, it could be useful to separate ripening tomatoes from the background, which is defined as green tomatoes, branches, leaves, soil, etc.



a) The line profile of ripen tomato



b) The line profile of background

Figure 2. The intensity of ripen tomato and background on short line

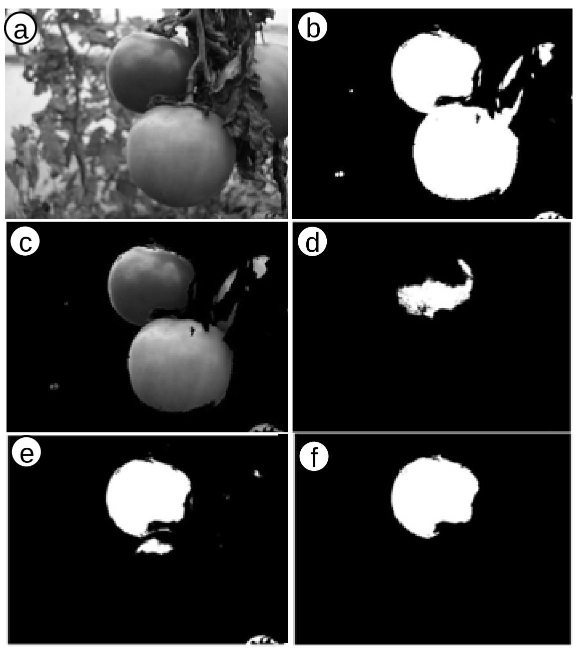


Figure 3. The algorithm of extracting ripe tomatoes in images. (a) original image (b) extracting background (c) removing background from original image (d) extracting red part (e) extracting the unripe part of tomatoes (f) extracting the ripe tomato

An apparent difference between the background and ripening tomatoes is in their colour. Figure 2 illustrates the *RGB* components of tomatoes and the background along a short line distance. The difference between red and green was obvious and could be used as a simple and positive factor for thresholding the image. The result of the thresholding is shown in Figure 3b as binary images with black coloured background. Figure 3a illustrates the original colour image. By multiplying the binary image on the three RGB components of the original image and then combining them, the final image after the processing was a colour image of tomatoes without background (Figure 3c).

The tomatoes in the resulting image are ripening tomatoes in different stages that should be separated. The main goal was to distinguish completely ripe tomatoes from the rest. The second part of the algorithm has been developed in three steps due to the complication introduced by the rather similar colour of tomato in different ripening stages, especially those at the end of ripening process.

The first step was separating the reddest part of tomato (Figure 3d). Naturally, the more ripe tomato, the bigger this part will be. The other colour space, *YIQ*, was used to achieve this purpose. In *YIQ* space, *Y* component represents the luminance while *I* and *Q* represent the chrominance information; with *I* stands for in-phase while *Q* stands for quadrature. The *YIQ* colour space obtains from *RGB* colour model by following linear transformation (Cheng et al., 2001).

$$\begin{bmatrix} Y \\ I \\ Q \end{bmatrix} = \begin{bmatrix} 0.299 & 0.587 & 0.114 \\ 0.596 & -0.274 & -0.322 \\ 0.211 & -0.253 & -0.312 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix} \tag{1}$$

Experiments showed that the best threshold value (T_1) for extracting the red part of tomato could be accessed by:

$$T_1 = (Y - I) < 0.01 \quad \& \quad Q > 0.08 \tag{2}$$

In the second step, after the ripe part of tomato was distinguished, the algorithm took into account the red and orange part of tomatoes. The *RGB* colour space was sufficient to provide a value for thresholding (T_2). Figure 3e illustrates the extracted part of tomatoes.

$$T_2 = R - (1.3G) \tag{3}$$

The results of these two steps were combined to distinguish ripe tomatoes. The result of the first step illustrates the ripe tomato part in the image, so it was used in the second step to remove the part in the image where the unripe tomatoes lay. The processed image was able to show the ripe tomatoes part but it would be much better if the algorithm could extract the whole ripe tomato. This is important for the adjustment of the arm of the harvest robot to open wide enough to securely catch the fruit. Thus, this issue is addressed in the following step.

The third step was extracting the yellow part, i.e. the missing part of the ripe tomato. In this step, the application of the *HIS* colour space was necessary, in addition to *YIQ* colour space. In *HIS* colour space, *H, I* and *S* represent the hue, intensity and saturation respectively and define as (Cheng et al., 2001):

$$\begin{aligned} H &= tg^{-1}\left[\frac{\sqrt{3}(G-B)}{(R-G)(R-B)}\right] \\ S &= 1-\frac{\min(R,G,B)}{I} \\ I &= \frac{R+G+B}{3} \end{aligned} \tag{4}$$

Experiments showed that the best threshold value (T_3) for extracting the yellow part of tomato is associated with Y and S:

$$T_3 = -1.2(Y - S) \tag{5}$$

By adding the yellow parts to the previously processed image, the whole part of ripe tomatoes was yielded but some yellow part was included to image as well. So the result of first step, i.e. extraction of the completely red part of tomato image was used to eliminate the superfluous yellow part.

The opening function used at the end to remove any small noise that could be in the final image (Figure 3f). It was helpful to remove image of the tomatoes from the next plant row in the greenhouse too.

RESULTS and DISCUSSION

The research showed that the lighting condition in greenhouse had significant effect on the image extraction process of ripe tomato. In the parts of the greenhouse where light was sufficient, the images were of good quality. In these images, it was easier to distinguish the ripe tomato from the unripe tomatoes. However, where light was insufficient, images were of lower quality and the colour of unripe tomato was darker, which hampered the detection of the ripe tomatoes.

In poor lighting condition, the *RGB* colour model alone is insufficient for extracting the ripe tomato. The RGB model is suitable for colour display, but not good for colour scene segmentation and analysis because of the high correlation among the *R, G* and *B* components (Pietikaimen, 1996; Littmann and Ritter, 1997). Consequently, if the intensity changes, all the three components will change accordingly. However, the intensity is a separate component in the *HIS* system, in which the colour information is represented by hue and saturation values, while intensity, which describes the brightness of an image, is determined by the amount of the light. Hue is particularly useful in the cases where the illumination level varies from point to point or image to image. If the integrated white condition holds, hue is invariant to certain types of highlights, shading and shadows.

Since, the lighting conditions were not controlled in this research, using the *HIS* colour model could be suitable. On the other hand, the *YIQ* colour model can partly get rid of the correlation of the red, green and blue components in an image, too (Cheng et al., 2001). Therefore, the correct recognition of ripe tomato was done using the composite of three *RGB*, *HIS* and *YIQ* colour models.

The algorithm of detecting ripe tomato was based on colour properties of objects (green, yellow, orange and red colour tomato, branches, leaves and greenhouse space) in image. Since the colour of ripe tomato and unripe tomato were close to each other, a simultaneous removal of the part of the unripe tomato and the background in the image was not possible. Moreover, in many cases, while removing unripe tomato, parts of the background exposed to the sunlight were extracted too, because the saturation value of the mentioned parts was higher than in other parts. So the background of unripe tomato was removed separately. For this purpose, the colour data of the background, the ripe and the unripe tomato were extracted and analysed. Since the *R-G* value of background was higher than the ripe and the unripe tomato, it was used for removing background.

The result of the previous process was an image that contains only ripe and unripe tomatoes. Since tomatoes were in a cluster, using a morphology model for extraction of ripe tomato was not feasible. Furthermore, none of the many established relationships in the *RGB* colour space was able identify ripe tomato. In addition, the intensity of some pixels in the ripe tomato was similar to the pixel intensity of the unripe tomato, so it is likely that the yellow-orange parts of ripe tomato were removed with the unripe tomato. Therefore, for extracting the ripe tomato, a combination of colour models has to be used. Many colour models were tested and finally a particular combination of *RGB, HIS* and *YIQ* colour models, yielded the best results. Figure 4 shows some examples of the original images and the result of the developed algorithm.

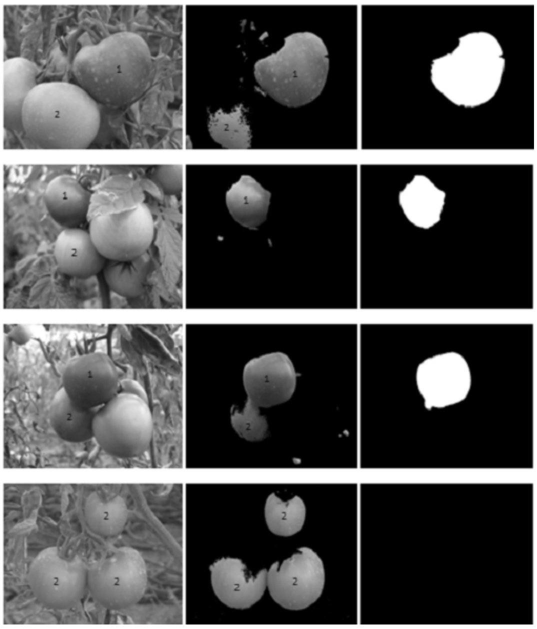


Figure 4. Some examples from developed algorithm. First column shows the original images, second column shows the images after removing the background and the extracted ripe tomato are shown in the last column. Ripe and unripe tomatoes were shown with the number 1 and 2 respectively.

Extracting the full area of the ripe tomato is important for designing the harvest robot. The results of analysis of about 200 images showed that the algorithm was able to extract about 92- 96% area of the ripe tomatoes in an image. For calculating the accuracy, the colour of a ripe tomato was changed to black manually. Then its area was compared with the area of the same tomato extracted by algorithm. One example is shown in Figure 5.

Although some images were taken in poor lighting, the accuracy of extracting ripe tomato was satisfactory.

In addition, it was necessary to eliminate all of the ripe tomatoes at the other growing row; otherwise the robot would be promoted to pick them by mistake. Since the ripe tomatoes at other rows looked smaller relative to tomatoes at the front row,the algorithm was modified to remove the extracted tomatoes as a noise when their size was smaller than a special value.

The proposed algorithm was able to analyse an image and to extract the ripe tomatoes of an image in about 1.25 s, which should be enough for a conventional harvesting system.

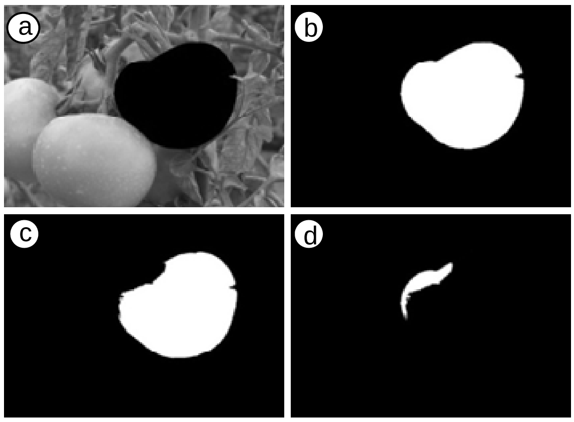


Figure 5. Calculating the accuracy of algorithm for extracting the area of tomato. (a) Manually coloured of ripe tomato (b) Real area of tomato (c) Extracted area of tomato by algorithm (d) The error

CONCLUSIONS

An algorithm was developed to automatically recognize the ripe tomato by a machine vision system. Colour data was extracted and a composite of RGB, HIS and YIQ colour models were used for recognizing the ripe tomatoes. The algorithm was tested under different lighting conditions of greenhouse, and it was successful in recognizing the ripe tomato. It consists of two steps, first removing the background in the image and then extracting the ripe tomatoes from the unripe ones. The accuracy of extracted tomato area was about 92-96% in the 200 tested images. This accuracy was high enough to use in automatic harvest systems.

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