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A methodology for fresh tomato maturity detection using computer vision

Peng Wan[a], Arash Toudeshki[b], Hequn Tan[a], Reza Ehsani[b,*]

[a] College of Engineering, Huazhong Agricultural University, No. 1, Shizishan Street, Wuhan 430070, China
[b] School of Engineering, University of California, Merced, CA 95343, USA

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A B S T R A C T

Recent advancements in computer vision have provided opportunities for new applications in agriculture. Accurate yield estimation of fruit and vegetable crops is very important for better harvesting and marketing planning and logistics. This paper proposes a method for detecting the maturity levels (green, orange, and red) of fresh market tomatoes (Roma and Pear varieties) by combining the feature color value with the backpropagation neural network (BPNN) classification technique. A maturity detection device based on computer vision technology was designed specifically to acquire the tomato images in the lab. The tomato images were processed and the targets of the tomatoes were obtained based on the image processing technology. After that, the maximum inscribed circle of the tomato's surface was identified as the color feature extraction area. The color feature extraction area was divided into five concentric circles (sub-domains). The average hue values of each sub-region were extracted as the feature color values and used to describe the maturity level of the samples. After that, the five feature color values were imported to the BPNN as input values to detect the maturity of the tomato samples. Analysis of the results shows that the average accuracy for detecting the three maturity levels of tomato samples using this method is 99.31%; and the standard deviation is 1.2%.

1. Introduction

The tomato is well known as one of the most popular fruits in the world. It is a rich source of fiber and vitamins A and C. Also, consumption of tomato has been associated with decreased risk of some cancers, cardiovascular disease, osteoporosis, and so on (Saad et al., 2016; Bhowmik et al., 2012; Chang et al., 2006; Takeoka et al., 2001). Worldwide, the tomato is also an important horticultural plant (Wei et al., 2016), and it is the most exported fleshy fruit (Van de Poel et al., 2012). Knowing the maturity level of tomatoes is important for different purposes such as priority of transportation to market and storage based on their maturity stage (Xiao et al., 2015). Traditionally, tomatoes are classified based on their physiological maturity by manual sorting (Van de Poel et al., 2012). However, manual sorting of the tomatoes and other fruits is a time consuming procedure. It depends on a person who has been specially trained in sorting tomatoes. This skill of the sorter varies from a person to person; therefore, it is not an accurate process (Satpute and Jagdale, 2016; Ehsani et al., 2016).

Color is an imperative quality characteristic of fruits. It represents the degree of maturity, sugar content, acidity, and taste. For instance, in fresh fruit market such as apples and peaches, darker red color represents higher quality fruit than does light red (Li et al., 2009). Color features have been widely applied for quality evaluation of apple, mostly for detecting imperfection. In this case, the color features of each pixel in the images obtained from three components of red, green, and blue spaces could be effectively used to segment defects of two varieties of apples (Leemans and Destain, 2004; Leemans et al., 1999, 1998). Tomato is a type of product whose color features are extensively used as a good indicator of recognizing the maturity level (Arivazhagan et al., 2010). The early applications of color features in tomato quality evaluation and sorting were preliminarily carried out by Choi et al. (1995), Moini and O'Brien (1978), and Stephenson (1976). Sarkar and Wolfe (1985) studied the method to classify green and red tomatoes based on the gray intensities of tomato images. A study on the relationship between tomato quality and maturity stage was carried out by Helyes et al. (2006).

Computer vision is a non-destructive method that can be used for inspection and has found to be applicable in both the food industry and precision agriculture, including the inspection and grading of fruits and vegetables (George, 2015; Xiao et al., 2015; Patel et al., 2012; Kondo, 2010; Sun, 2000). Color sorting and grading of fruits and vegetables by computer vision methods has become the main way by which to maintain the quality and increase the value of the salable products. Color grading and sorting by computer vision has been developed for several fresh market products such as apple (Bhatt and Pant, 2015; Li et al., 2002), mango (Nagle et al., 2016; Bejo and Kamaruddin, 2014),

* Corresponding author.
E-mail address: rehsani@ucmerced.edu (R. Ehsani).

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banana (Chen and Chang, 2016; Sanaeifar et al., 2016), sweet pepper (Jun et al., 2012), potato (Tavakoli and Najafzadeh, 2015), and cucumber (Guoxiang et al., 2016). Tomato maturity is closely related to its surface color features. Thus, evaluating the levels of tomato maturity by analyzing the surface color features of tomato by computer vision seems to be feasible.

To improve the speed and accuracy of tomatoes grading, research has been conducted on the grading methods. Arjenaki et al. (2013) published a study on inline tomato sorting based on shape, maturity, size, and surface defects using machine vision, their results showed that defect detection, shape algorithm, size algorithm, and overall system accuracies were 84.4%, 90.9%, 94.5%, and 90%, respectively. However the accuracies of tomato classification can also be improved. Laykin et al. (2002) developed image processing algorithms to provide quality parameters such as color, color homogeneity, defects, shape, and stem detection for tomato classification. The experiments resulted in 90% correct bruise classification with 2% severely misclassified, 90% correct color homogeneity classification, 92% correct color detection with 2% severely misclassified, and 100% stem detection.

The majority of the previous research on detecting the maturity of tomato has been done for sorting applications. In most of the reported works, classification was done only to distinguish between red and green tomatoes. However, the fresh tomato market requires to detect only physiologically mature green (greenish-orange color) yield, which occurs between bright green and red maturity levels. This maturity level of tomato has a longer shelf life than red tomatoes and it is very suitable for post-harvest storage.

The objective of this study is to develop a color analysis method for calculating the feature color values of fresh market tomato and then utilize BPNN to sort tomatoes based on the color features with potential future application in in-field yield estimation.

2. Materials and methods

2.1. Tomato samples

Two tomato varieties were chosen for this study: (i) Roma; (ii) Pear (Lycopersicon esculenta) which were planted in Myakka City, Florida, USA. More than 200 samples per variety were picked randomly based on plant maturity. After being picked, they were taken to the lab and the images of 150 tomato samples for each variety were acquired, after eliminating the damaged samples during the transportation and the too small samples. The different varieties and maturity levels of the tomato samples are shown in Fig. 1.

As it is shown in Table 1, in order to form a set of 150 samples, 50 images were captured for each variety of tomato. Then, this set was divided into two groups. The first group was selected as the training set, which consisted of 102 samples and contained 34 samples of each maturity level. The second group was selected as the known detection control. This group consisted of 48 samples, and 16 samples for each maturity level of the tomato samples were obtained. The samples in the training set were used to build the recognition model, and the samples in the detection set were used to verify the accuracy of the model.

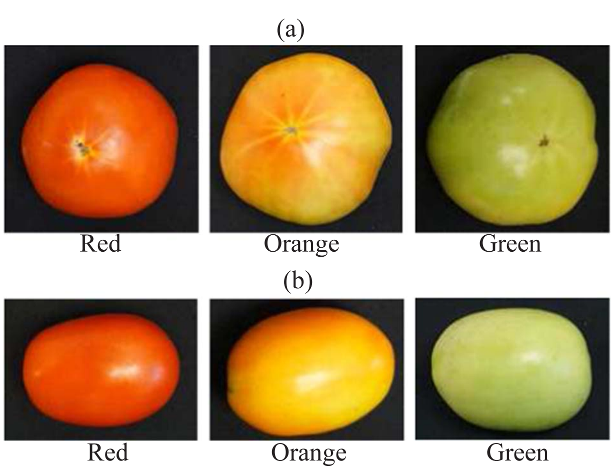

Fig. 1. Example of maturity levels (red, orange, and green) of (a) Roma tomato (large), (b) Pear tomato (smaller). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

2.2. Computer vision system

The experiments for detecting the required features were conducted in the lab under the normal fluorescent light sources. The equipment set-up for image collection is shown in Fig. 2. The camera (SONY NEX-5N, Tokyo, Japan) with lens zoom of between 18 and 55 mm (Optical Steady Shot, Sony, Tokyo, Japan) was installed in the top of the tripod, and the distance between the lens of the camera and the objects was adjusted to 40 cm. The desk was covered with a black cloth as a dark background onto which the tomato samples were placed. All fluorescent lights were turned on while capturing the images of the tomato samples for more uniform light and sufficient illumination.

An image-processing program was developed using Visual C + + 6.0 on a Microsoft Windows XP operating system (CPU: core i3, 2.8 MHz, memory: Kingston, 2 GB) and the Matrox Imaging Library 9.0 (Matrox, Inc., Dorval, Canada). The image processing program was designed to filter the images of tomato samples (Li et al., 2013; Gibson and Nguyen, 2013), segment the background of the images (Mizushima and Lu, 2013; Peng et al., 2013) and extract the eigenvalues of the tomato from the images (Ghimire and Lee, 2013; Singha and Hemachandran, 2012).

2.3. Image processing

In this study, a machine vision algorithm was developed to capture the images of the tomato samples, and then it extracted the feature color value to classify the maturity level of the tomato samples. The detection flow chart of the tomato maturity level, based on the machine vision, is shown in Fig. 3.

Capturing the tomato images at first was based on the machine vision system, and then the tomato images were preprocessed to obtain the desired tomato images. In the next process, the color values of the tomato samples from the desired tomato images were extracted, and the color models of all color values were transformed. Then, the color feature values of the tomato samples were calculated. Finally, based on the color feature values, a BPNN model was built to identify the maturity of the tomato samples using classification.

As shown in Fig. 3, before extracting the color values of the tomato samples, the tomato images must be preprocessed and the tomato areas need to be segmented from the background of the unprocessed tomato images. Some image processing algorithms such as threshold segmentation, noise cancellation, image contour extraction and boundary fill algorithm, were used to process the images of the tomato samples. The segmentation flow chart of a tomato image is shown in Fig. 4.

In this process, the tomato sample images were segmented using the threshold segmentation algorithm previously used by Al-Amri et al. (2010) and Zhu et al. (2007, 2010). After that, the preliminary binary images of the tomato samples were extracted. Subsequently, the black pixels were removed using the noise point cancellation algorithm of Jayasree et al. (2013) and the binary images of the tomato samples with a clear background were extracted. The contours of the binary images of the tomato samples were extracted using the contour tracking algorithm previously was reported by Li et al. (2013). Then, the contours of the binary images of the tomato samples were filled using Shao et al. (2012) seed filling algorithm, and the whole binary images of the tomato samples were attained. As a result, the tomato targets were segmented from the denoised background of the tomato sample images. The preprocessing steps performed on the tomato samples are shown in

Table 1
Number of tomato samples used for training and detection sets.

Tomato variety	Samples per each maturity level						Training	Detection	Total
	Red		Orange		Green				
	Training	Detection	Training	Detection	Training	Detection			
Roma	34	16	34	16	34	16	102	48	150
Pear	34	16	34	16	34	16	102	48	150

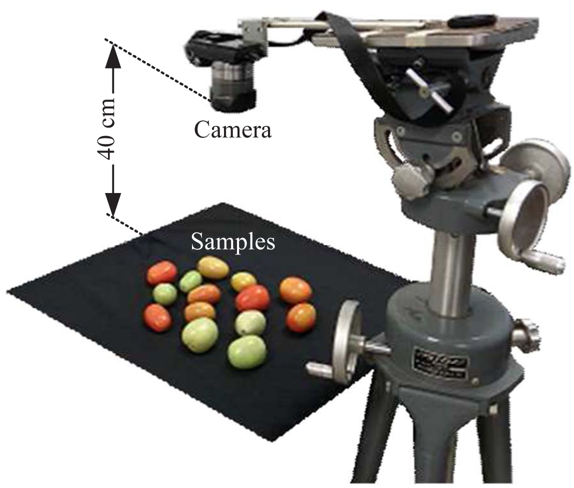

Fig. 2. The tomato image capturing set-up.

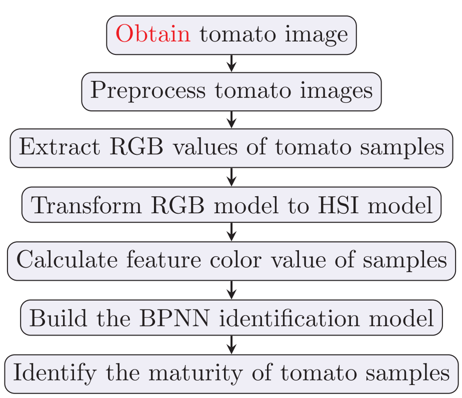

Fig. 3. The detection flow chart for tomato maturity based on machine vision.

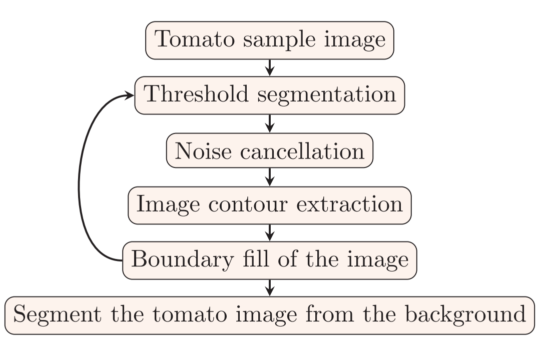

Fig. 4. The preprocessing flow chart for the tomato image.

Fig. 5.

2.4. Color feature extraction

In order to obtain the color values of the tomato samples, we used an equal-area dividing method to divide the surface area of the tomato sample into five regions and extract the red (R), green (G), and blue (B), referred to as the RGB values of each region, and then convert the RGB color values into the hue (H), saturation (S) and intensity (I), referred to as HSI color values. Before this process, the surface area of the tomato samples was divided in order to calculate the centroid of the tomato images by image processing technology to determine the contour of the tomato images.

The coordinates of the pixel point for the tomato target image was expressed as $\{(x_i,y_i)|0 \leqslant i \leqslant M\}$, where $M$is the total number of pixel points in the tomato target image, as shown in Fig. 6:

The centroid coordinates of the tomato target image $O(X_0,Y_0)$ are expressed in Eq. (1):

$$\begin{cases} X_0 = \frac{1}{M}\sum_{i=0}^{M} x_i \\ Y_0 = \frac{1}{M}\sum_{i=0}^{M} y_i \end{cases} \tag{1}$$

Next, the tomato target image was centered using the centroid coordinate as the center point. By calculating the distance from each point in the contour of the tomato images to the center point, the distance from the center of the tomato L_i is derived as:

$$L_i = \sqrt{(x_i-X_0)^2 + (y_i-Y_0)^2} \tag{2}$$

where i is the number of the contour points on the tomato image, and $0 \leqslant i \leqslant M$, where M is the total number of pixel points in the tomato target image.

By assuming that L_{min} is the minimum distance from the center to the edge of the counter (L_i), the circular shape with radius $r$can be determined by the minimum L_{min}, which is the inscribed circle with a maximum radius of r_{max}in the contour region of the tomato sample. This circular region is the extraction area for color values of the tomato samples. In order to divide the region of the inscribed circle into five sub-regions with equal area, used for extracting the feature color area (FCA), the core of the inscribed circle is defined as the center as well as the concentric circles with different radii r_i where i is an integer value between one and five. The relationship between the core of the tomato images, the contour of the tomato images, the maximum inscribed circle, and the radius of five sub-regions is shown in Fig. 7.

Therefore, the area between the FCAs is equal. This means that each FCA theoretically has the same number of pixels. Based on this assumption, the relationship between the area of the five sub-regions of the FCAs and the area of the maximum inscribed circle is:

$$\pi \times r_i^2 = \frac{i}{5} \times \pi \times r_{max}^2 \tag{3}$$

Thus, the relationship between the radius of the five sub-regions of the FCAs and the radius of the maximum inscribed circle is:

$$r_i = \sqrt{\frac{i}{5}} \times r_{max} \tag{4}$$

After the desired tomato image was separated from the background, firstly, the FCA of each tomato was identified, and then the color feature values were extracted. The schematic diagram of the FCA of two

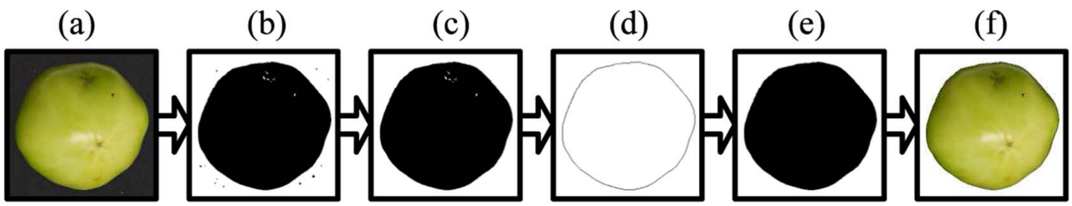

Fig. 5. The chart of preprocessing steps for segmenting the tomato image from a noisy background: (a) the tomato sample image; (b) after the threshold segmentation process; (c) after the noise cancellation process; (d) after the contour extraction process; (e) after the seed filling process; and (f) after the segmentation of the tomato image from the background.

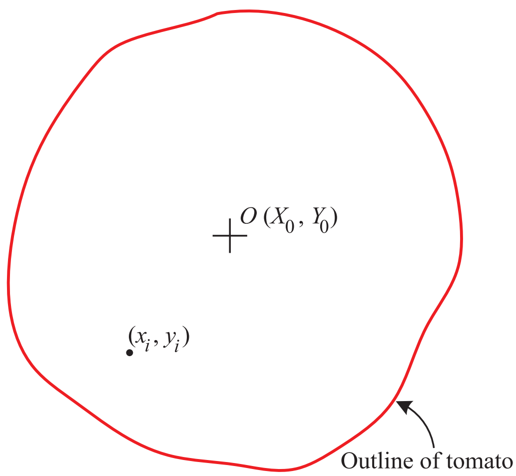

Fig. 6. The coordinates of the pixel point and the centroid coordinates of the tomato image.

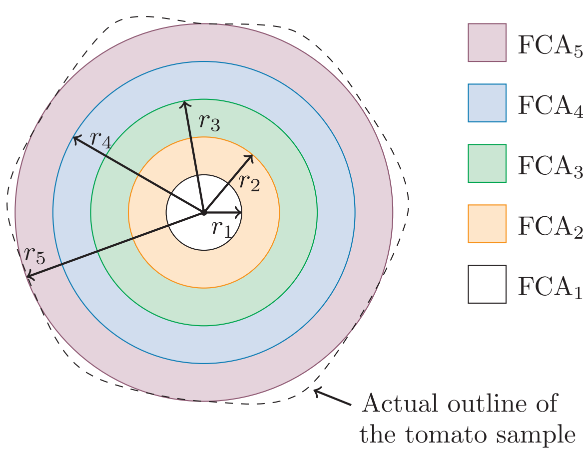

Fig. 7. The five feature color areas and the maximum inscribed circle of a tomato sample. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

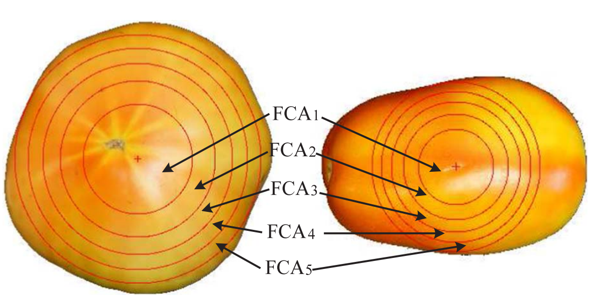

Fig. 8. The schematic diagram of the feature color extraction region. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

types of tomato samples is shown in Fig. 8.

The RGB color values can be extracted from the five sub-regions of the FCAs by using:

$$\begin{cases} \overline{R}_i = \frac{1}{n_i}\sum_{j=0}^{n_i} R_{ij} \\ \overline{G}_i = \frac{1}{n_i}\sum_{j=0}^{n_i} G_{ij} \\ \overline{B}_i = \frac{1}{n_i}\sum_{j=0}^{n_i} B_{ij} \end{cases} \quad (5)$$

where the $\overline{R}_i$, $\overline{G}_i$, and $\overline{B}_i$are the average values of the RGB color values for all the pixel points in the five sub-regions, i is the number of the five FCAs and is an integer varies between one and five, j is the number of pixel points in the five FCAs, and n is the total number of the pixel points in the five FCAs.

The tomato images are obtained using an RGB charge-coupled device (CCD) camera. However, the human vision is sensing based on the HSI color format which describes the color by using the HSI color values. Moreover, the HSI color mode is dependent on the hardware features, and it has little sensitivity to the light source. This work describes the color space of tomato samples with RGB, HSI, and the conversion relationships between these color spaces as:

$$\begin{cases} I_i = \frac{R+G+B}{3\times 100} \\ S_i = 1-\frac{min\{R,G,B\}}{I_i\times 100} \\ H_i = \cos^{-1}\left(\frac{0.5\times((R-G)+(R-B))}{\sqrt{(R-G)^2+(R-B)\times(G-B)}}\right) \end{cases} \quad (6)$$

where i represents the integer number of the five FCAs and i is an integer from one to five. Thus, the color values (CV) in five sub-regions of the tomato samples can be described as:

$$CV_i = (R_i,G_i,B_i,H_i,S_i,I_i) \quad (7)$$

where i represents the integer number of the five FCAs which is an integer between one and five.

Finally, in order to identify the maturity level of the tomato samples, concerning the variation of the color values in different tomato samples, the color values with the most significant effect were selected.

2.5. Identification method for tomato maturity level

The backpropagation neural network (BPNN) is derived from the artificial neural network (ANN) technique developed by Rumelhart et al. (1985). The inclusion of BPNN increases the accuracy of prediction through its consideration of the interaction between inputs and outputs. This makes it a more effective model of evaluation than traditional discriminant analysis and multiple logistic regressions (Hecht-Nielsen, 1989). The BPNN has been used for the variety classification and identification of some agricultural products (Kurtulmus et al., 2016; Wan et al., 2016) and other aspects such as management associate work retention for small and medium enterprises (Chen and Chang, 2016; Wang and Shun, 2016).

The BPNN was used to classify the detected maturity level of the tomato samples. Respectively, two types of tomato samples with three maturity levels were selected to be used as samples for image analysis process and obtain the feature color values to build the sample set of the neural network training set. The detection values were defined for a red tomato (RT), a mature tomato (MT), and a green tomato (GT) to be at 1, 2, and 3, respectively. Hence, the goals set for the neural network training set are 1, 2, and 3. Respectively, 40 other tomato samples were selected from three maturity levels to obtain the color feature values in order to build the detection set of the neural network.

Here, the BPNN consists of three layers. The neuron number of the input layer is five. Therefore, these are the number of the feature color values of tomato samples. The neuron number of the output layer is 1, and the output signals are 1, 2, and 3 which signify the RT, MT, GT tomato samples, respectively. The neuron number of the hidden layer is confirmed according to the accuracy of the test results by using MATLAB 2016a and the test set. The neural network identification function is defined as the logarithmic function:

$$f(x) = \frac{1}{1 + \exp(-x)} \tag{8}$$

3. Results and discussion

3.1. Divide the maximum inscribed circle into the feature color areas

The circle with the largest radius was defined as the maximum inscribed circle in the contour region of each tomato sample. The region was divided into five equal parts using the red circles. The code names for the FCAs of the tomato samples from the inner circle to the cylindrical were FCA_1, FCA_2, FCA_3, FCA_4, and FCA_5. The number of total pixels contained in the FCA is calculated as:

$$FCA_{total} = \sum_{i=1}^{5} FCA_i \tag{9}$$

The relationship between the number of pixels contained in the FCAs and the number of pixels contained in the outline of the tomato samples are presented in Table 2.

It is important to state that the average number of pixels contained in the outline of the Roma tomato samples was 71,634 and the average number of pixels contained in the outline of the Pear tomato samples was 36,902.

Therefore, by using the method of dividing the maximum inscribed circle into five equal FCAs can confirm that the distribution of pixel points in every FCA is almost equal.

3.2. Extraction of the feature color values of the tomato samples

After dividing the maximum inscribed circle into the five FCAs, the ranges of the RGB and HSI feature color values, 24 samples per each maturity level for two sizes of tomatoes were calculated. It was found that there are some changing occurred between the feature color values of different tomato samples. Thus, these changing rules for the feature color values in the FCAs of different tomato samples are graphically shown in Fig. 9.

Results show that in both Roma and Pear samples, recognizing the maturity level of the tomato from the B and H values is simpler than from the other feature color values. The I value is a good linear indicator, but only for Pear tomato samples. Here, the foremost focus is to find a significant linear indicator that works for both Pear and Roma tomato samples. Therefore, compared with the B value and the H value, which behave similarly in both Roma and Pear tomato samples, the I value is not a good candidate for this scope. The B value shows that it decreases almost linearly when the maturity level of the tomato changes from green to orange and from orange to red. A similar result is also observed for the H value. This amount of change in the H value is very remarkable. The same pattern occurs for all radii. Based on this finding, in order to recognize the ripeness of tomatoes, we would only need to monitor the B and the H values and neglect changes in the R and G values and the saturation and intensity values. This is due to the fact that recognizing the ripeness changing is more significant in B and H values than in the other values. Therefore, by minimizing the number of inputs from six to only two values for neural network classification, the data processing time will significantly be reduced and the result based on these two recognizable inputs can be more reliable than using six complex input values.

3.3. Identification of tomato maturity level

In order to train the BPNN, the training set is established using the feature color values of B and H for 102 samples per each variety of tomato with different sizes. Next, the BPNN is verified through the feature color values of B and H for 48 samples of two types of tomatoes. The detection results of the neuron number of different hidden layers are shown in Table 3.

Based on the results in Table 3, overall, when the input data of the H values are used as the feature color values, the accuracy rate of tomato samples maturity level identification is higher than when the input data of the B values are used as the feature color values. When the neuron number of hidden layers (NHL) is 10, the overall accuracy rate of tomato samples maturity level identification occurs at its highest amount. The accuracy rate of both red and mature tomato samples is 100.00%. The accuracy rate for the green tomato samples is 97.92%, and the average accuracy rate of tomato samples is at 99.31%. The identification results from the different maturity level of the tomato samples are shown in Fig. 10.

Fig. 10 shows the identification result of BPNN for B and H values. In this figure, these values are statistically analyzed for the Pear and Roma varieties. In this analysis, the B and H values were the input data and the neuron number of the hidden layer was 8, 10, and 12. It was found that the identification results for the maturity of the tomato samples using the BPNN are more dispersed and have more error. It is especially true when the maturity of the tomato samples is at the orange level; the value of the identification results ranges from one to three, which is the largest error. The value of the identification results is concentrated around one when the maturity of the tomato samples is red and the error is small. However, when the maturity of the tomato samples is green, the value of the identification results ranges from two to three which is a large error. But, when the H value of the feature

Table 2
The relationship of the pixel points contained in the equal area circles of the tomato image.

Tomato variety	Item	FCA_1	FCA_2	FCA_3	FCA_4	FCA_5	FCA_{total}
Roma	FCA(pixels)	12,198	12,216	12,213	12,200	12,189	61,016
	Percentage of average area of sample image	17.03%	17.05%	17.05%	17.03%	17.02%	85.18%
	Percentage of total FCA	19.99%	20.02%	20.02%	19.99%	19.98%	100.00%
Pear	FCA(pixels)	5051	5060	5065	5043	5050	25,269
	Percentage of average area of sample image	13.69%	13.71%	13.73%	13.67%	13.68%	68.48%
	Percentage of total FCA	19.99%	20.02%	20.04%	19.96%	19.98%	100.00%

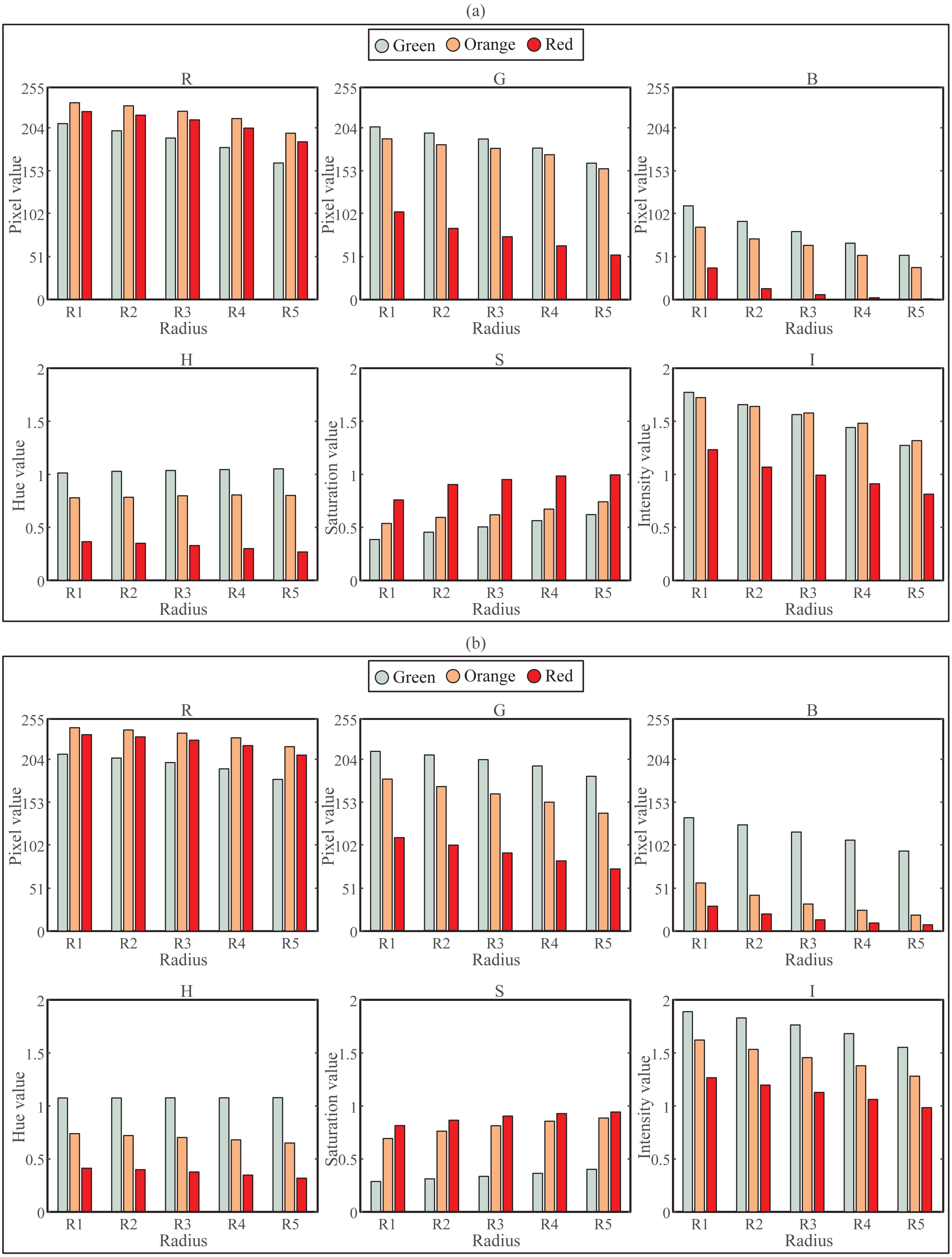

Fig. 9. The feature color values in (a) Roma tomato samples and (b) Pear tomato samples.

color values of the tomato samples is the input data and the neuron number of the hidden layer is 8, 10, and 12, the identification results for the different maturity of the tomato samples using the BPNN are better concentrated around the detection values. The detection value of the red tomato samples is concentrated around one, the detection value of the mature tomato samples is concentrated around two, and the

Table 3
The color detection results of the tomato samples using a back propagation neural network.

Tomato samples		The neuron number of hidden layers and the detection results					
		Blue(8)	Blue(10)	Blue(12)	Hue(8)	Hue(10)	Hue(12)
Red	Number of tomato samples	42	48	48	48	48	47
	Accuracy rate (%)	87.50%	100.00%	100.00%	100.00%	100.00%	97.92%
Orange	Number of tomato samples	32	20	32	45	48	45
	Accuracy rate (%)	66.67%	41.67%	66.67%	93.75%	100.00%	93.75%
Green	Number of tomato samples	45	45	45	46	47	48
	Accuracy rate (%)	93.75%	93.75%	93.75%	95.83%	97.92%	100.00%

detection value of the green tomato samples is concentrated near three, and the errors are less than the errors using the BPNN when the B value is the input data. Thus, comparing the B and the H values of the feature color values, shows that the detection results of the H value as the input data using the BPNN is better than the detection results of the B value. When the B value is the input data and the neural number of the hidden layer is 10, the detection value of the green tomato sample is concentrated around three; the errors are less than the detection value when the neural number of the hidden layer is 8 or 12. At the same time, the detection values between the tomato samples of different maturity using the BPNN do not overlap. Therefore, identifying the maturity level of the tomato samples can achieve a satisfactory result by constructing a three layered BPNN with five neurons in the input layer, ten neurons in the hidden layer, and one neuron in the output layer and the discriminate function of the logistic-type function.

4. Conclusions

In this study, a method utilized for detecting the tomato maturity level of the Roma and Pear varieties was verified by experiments based on the color feature and BPNN. First, the tomato images were obtained by a machine vision system. Next, the desired tomato images were segmented from the tomato images based on the developed image processing technique, and after that, the maximum inscribed circles on the surface of the tomatoes were used to determine the feature color extraction region. Next, the feature color extraction region was divided into five feature color sub-regions of the same area with concentric circles of different radii. The RGB and HSI feature color values were extracted from the FCAs. Then, the B and H color values of the FCAs were regarded as the color feature value of the tomato. Finally, a BPNN with three layers was adopted to classify the maturity level of two different tomato varieties. The results of this research show that the accuracy rate for this method of extracting the H values of the tomato image and then detecting and classifying the maturity levels of the tomato samples is 99.31%, which was anticipated. Finally, the results of this study have proven that utilizing the advantage of BPNN for classification of tomatoes based on their color features can potentially be applied for in-field yield estimation of fresh tomatoes.

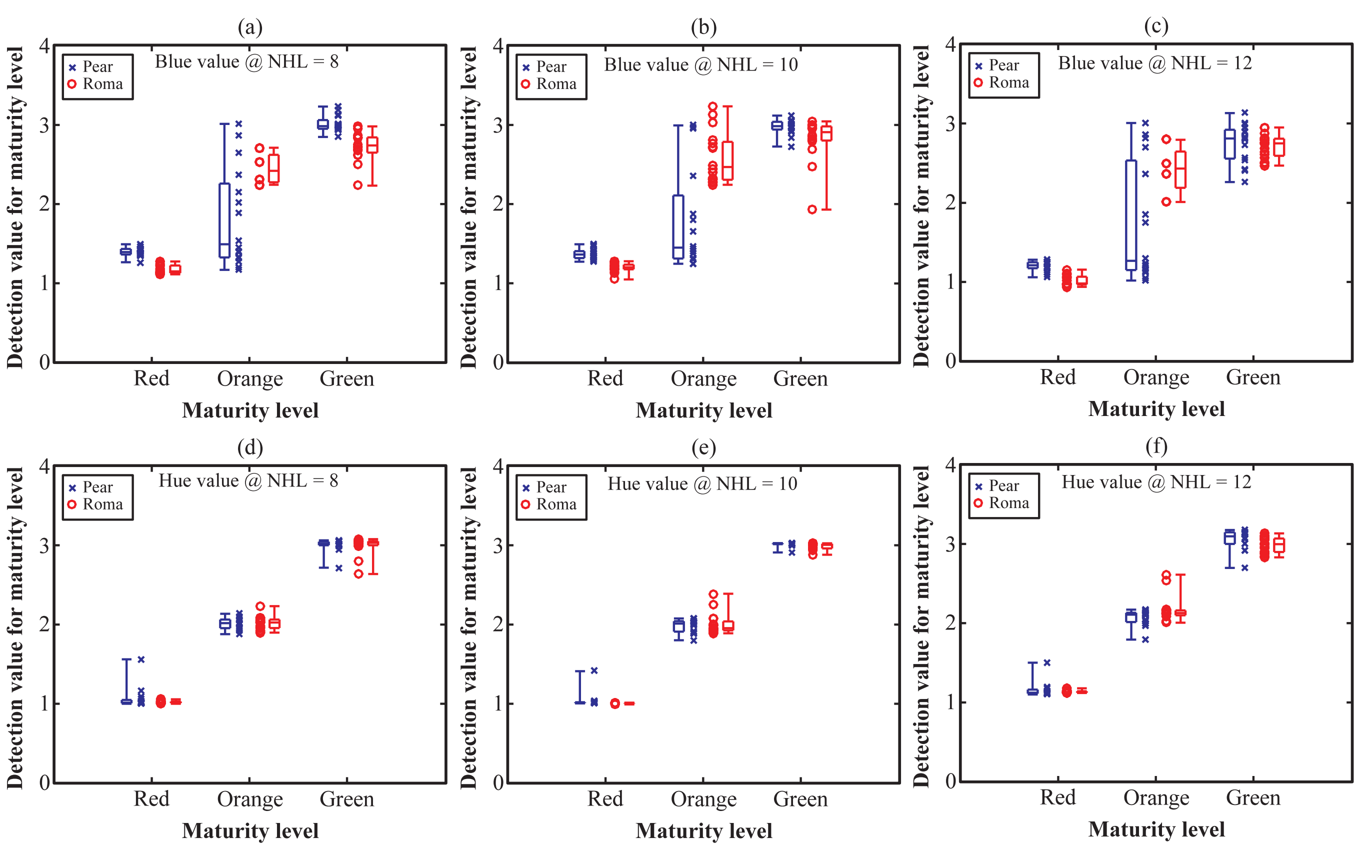

Fig. 10. The identification result of BPNN for B value where the (a) NHL is 8, (b) NHL is 10, and (c) NHL is 12; and for H value where the (d) NHL is 8, (e) NHL is 10 and (f) NHL is 12.

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