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A methodology for fresh tomato maturity detection using computer vision

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ABSTRACT

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),

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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.

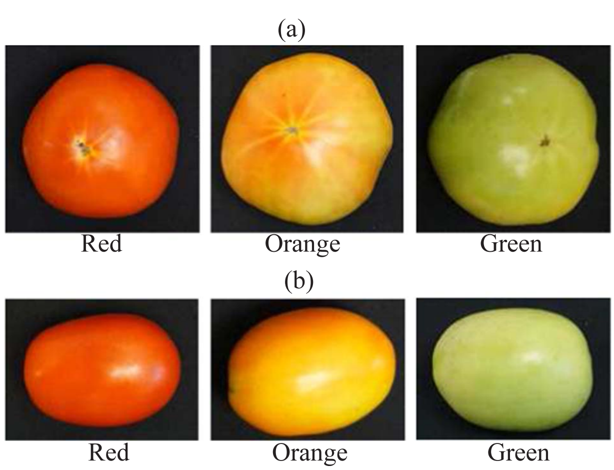

Fig. 1. Example of maturity levels (red, orange, and green) of (a) Roma tomato (large), (b) Pear tomato (smaller). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

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