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Machine vision system for grading of dried figs

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ABSTRACT

Fig is a horticultural product which requires sorting at the postharvest stage before being marketed. In this study, a grading system based on machine vision was developed for grading figs. The system hardware was composed of a feeder, a belt conveyor, a CCD camera, a lighting system, and a separation unit. Three quality indices, namely color, size, and split size, were first classified by fig-processing experts into the five classes. Then, the images of the fig samples were captured using a machine vision system. First, the length of pixels in each image and longitudinal coordinates of the center of gravity of fig pixels were extracted for calculating the nozzle eject time. For extracting the three quality indices of each class, a machine vision algorithm was developed. This algorithm determined color intensity and diameter of each fig as the indicators of its color and size, respectively. For calculating the split area, the images were first binarized by using the color intensity difference between the split and other parts of the fruit in order to determine the area of the split section. A grading algorithm was also coded in Lab-VIEW for sorting figs based on their quality indices extracted by the image processing algorithm into five qualitative grades. In the grading algorithm, the values of these features were compared with the threshold value that was predetermined by an expert. Results showed that the developed system improved the sorting accuracy for all the classes up to 95.2%. The system's mean rate was 90 kg/h for processing and grading figs.

1. Introduction

The common fig (*Ficus carica* L.) is a species of Moraceae family, native to the Mediterranean and western Asian. Some varieties of Iranian edible figs are Izmir, General, and San Pedro. Iran is the third largest producer and exporter of figs in the world and has ranked fourth in terms of cultivated area after Portugal, Egypt, and Turkey. With regard to the amount of production, after Egypt and Turkey, Iran possesses the third place in the world (FAO, 2012). Cultivation area of figs in Iran is 44293.6 ha, both dried and irrigated, with the total production of 57,057 ton (Anon., 2010).

Figs are an excellent source of minerals, vitamins, and dietary fibers; they are free from fat and cholesterol and contain a high amount of amino acids (Slavin, 2006; Solomon et al., 2006). Figs are cultivated in tropical and semi-tropical areas. They also contain high levels of flavonoids, polyphenols, and anthocyanins, which are essential for human health (Slavin, 2006; Solomon et al., 2006). Phenolic acids and flavonoids of three kinds of Mediterranean figs were investigated by Veberic et al. (2008).

In today's competitive market, producers have to present their products sorted according to their physical characteristics (including appearance, size, color, and internal health), since consumers tend to use healthy and homogenous products. Fruit sorting can increase uniformity in size and shape, reduce packaging and transportation costs, and provide an optimum packaging configuration (Tabatabaeefar et al., 2000).

It is very difficult to manually sort and separate this product. Manual inspection involves labor-intensive work and decision-making can be very subjective depending on the mood and condition of process stakeholders. Furthermore, this manual procedure can be very time-consuming and inefficient, especially when dealing with high production volumes.

In most early mechanical sorting machines, grading was done based on product size (generally diameters). However, these machines were not able to analyze and grade products based on their appearance and internal properties. Moreover, they could cause mechanical damage to the products (Amiriparian et al., 2008; Mc Rae, 1985).

Considering this background, new grading methods like machine vision systems have been introduced. These non-destructive and online systems would be a promising tool for the purposes of quality control as well as product inspection, sorting,

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and grading. Nowadays, a number of studies have increasingly used this technology for sorting fruits based on their external properties (Chen et al., 2002; Blasco et al., 2003, 2008; Rocha et al., 2010).

A machine vision system has several components: a sequencing unit, conveyer belts, a CCD camera, a separation unit, an image processing algorithm, and a grading algorithm. Abdelhedi et al. (2012) designed and developed an online machine vision inspection system for a high speed conveyor. A special effort was made to design defect detection algorithms in order to achieve two main objectives: accurate feature extraction and online capabilities, while both considering robustness and low processing time. The use of well-defined shooting conditions also allowed for a simplified image processing technique.

Heinemann et al. (1996) and Noordam et al. (2000) have developed an automated machine vision system for the shape-classification of potatoes. Blasco et al. (2009) developed a machine vision-based system for inspecting and sorting mandarin segments by extracting morphological features for their grading into commercial categories. Their results showed that the machine can correctly classify at 93.2% accuracy. An image processing algorithm was used for segmenting objects from the background and, then, extracting their features. The extracted features were color, shape, size, and texture. Color features were extensively applied for apple quality evaluation, mainly in defect detection (Leemans et al., 1999; Leemans and Destain, 2004). To separate open-mouth pistachio, Pearson and Toyofuku (2000) conducted a study and separated damaged, open-mouth, and closed-mouth pistachios using their color characteristics with the accuracy of 95%. Nasirahmadi and Behroozi-Khazaei (2013) also used machine vision for identifying bean varieties according to color features. Arjenaki et al. (2013) investigated an image processing algorithm for extracting shape, size, and color features for sorting tomatoes accordingly.

Determination of toxigenic fungi and different aflatoxins in dried figs has been reported in different countries due to the significant health risks associated with aflatoxins in foods (Iamanaka et al., 2007; Senyuva et al., 2007; Javanmard, 2010). Because skin damage occurs on the fruit at harvest, preventing fruit skin damage is essential to maintain the postharvest life limitations of fresh fig fruit, investigate the shelf life of fruit with varying degrees of skin damage, and evaluate the benefits of regulated deficit irrigation on reducing fruit skin damage, as was considered by Kong et al. (2013). Figs were qualitatively assessed using near-infrared spectroscopy in the study by Burks et al. (2000). The figs were classified into insect-infested, rotten, sour, and dirty defect categories. Classification accuracy for these categories ranged from 83% to 100%. Souri et al. (2011) designed and developed a moisture-based fig sorter. Based on some physical properties of figs affected by moisture content, coefficients of static friction and rolling resistance were introduced as key characteristics in fig sorting. Results showed that both conveyor incline and speed had highly significant effects on sorting accuracy. The best sorting accuracy (about 80%) occurred at the speed of 9.4 m min^{-1} and incline of 8, 9, 10 degrees. Using machine vision for grading figs was reported by Benalia et al. (2013), who sorted figs into three classes only based on color features.

In the literature review, little information can be found about fig sorting. Figs need to be graded before being marketed. Considering the disadvantages of traditional grading practices and mechanical machines, a machine vision grading system was designed, developed, and evaluated to classify figs based of their size, color, and split degree, which were taken from the behavior analysis of the fig markets.

2. Materials and methods

2.1. Sample preparation

In this study, the figs were collected from the world's largest fig forests in Neyriz and Estahban, Fars Province, Iran. Most kinds of the figs in these regions included Izmir and Green varieties, which are late variety, yellow–green, and dried fruits. The color, size, and split amount of the fig were considered an acceptable attribute for marketing. Based on these physical properties and standards developed by Institute of Standards and Industrial Research of Iran (National Standard, 16539) and also the questionnaires which were distributed among gardeners and distributers, the figs were divided into five grades: Grade I (G1), Grade II (G2), Grade III (G3), Grade IV (G4), and Grade V (G5) (Fig. 1). In this study, 500 images were totally obtained.

2.2. Real-time grading system for dried figs

In this research, a fig grading system was designed and developed, which consisted of feeding, machine vision, and grading units. These sections are introduced below.

2.2.1. Feeder

The feeding unit was placed before the lighting chamber and the figs were placed with spacing on the conveyor belt. The time required to determine the grade of each fig was 180 ms; *i.e.* 141 ms for image processing (imaging and processing) and 39 ms for grading control program. Since it took 180 ms for imaging, processing, and grading, the feeder had to feed a fig every 180 ms into the imaging chamber; thus, grading was about 5 figs per second and the feeding rate was 5 figs per second. For this purpose, the feeder was designed to include a dispenser, a DC motor, feeding conveyors, and a hopper (Fig. 2).

The dispenser was capable of placing 3 figs on the conveyor belt per rotation (dispenser capacity). Considering that the feeding rate was 5 figs per second, the DC motor's speed required for rotating the fluted metering device was obtained as follows:

$$\text{Rotate per second} = \frac{\text{Product feed rate}}{\text{Dispenser capacity}} \tag{1}$$

Speed of DC motors = $\frac{5}{3}$ = 1.67 rps or 100 rpm

2.2.2. Arrangement of conveyors

A set of conveyors was designed to separate and put figs in a straight line before feeding them into the imaging chamber. Fig. 3 shows the formation of figs into a row. The figs were moved onward by the conveyor to enter the queuing unit in one queue. The queued figs were completely separated due to the speed difference between the feeding and detecting conveyors.

Movement speed affects the level of image blurring. Thus, for preventing blurring in images caused by the movement of figs on the conveyor, the detection conveyor's speed was set to 30 cm/s. The feeding conveyer speed was less than that of the detection conveyer with 2.5 ratio.

$$\text{Speed ratio} = \frac{\text{Detection conveyor}}{\text{Feeding conveyor}} = 2.5$$

$$\text{Linear speed of feeder conveyor } (V) = \frac{\text{Detection conveyor}}{\text{Speed ratio}} = \frac{30\ \text{cm/s}}{2.5} = 12\ \text{cm/s}$$