Computers and Electronics in Agriculture 119 (2015) 158–165

Contents lists available at ScienceDirect

Computers and Electronics in Agriculture

journal homepage: www.elsevier.com/locate/compag

Original papers

Machine vision system for grading of dried figs

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ARTICLE INFO

Article history:
Received 26 February 2015
Received in revised form 26 August 2015
Accepted 25 October 2015
Available online 6 November 2015

Keywords:
Dried figs
Machine vision
Grading
Image processing

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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http://dx.doi.org/10.1016/j.compag.2015.10.019
0168-1699/

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.

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

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

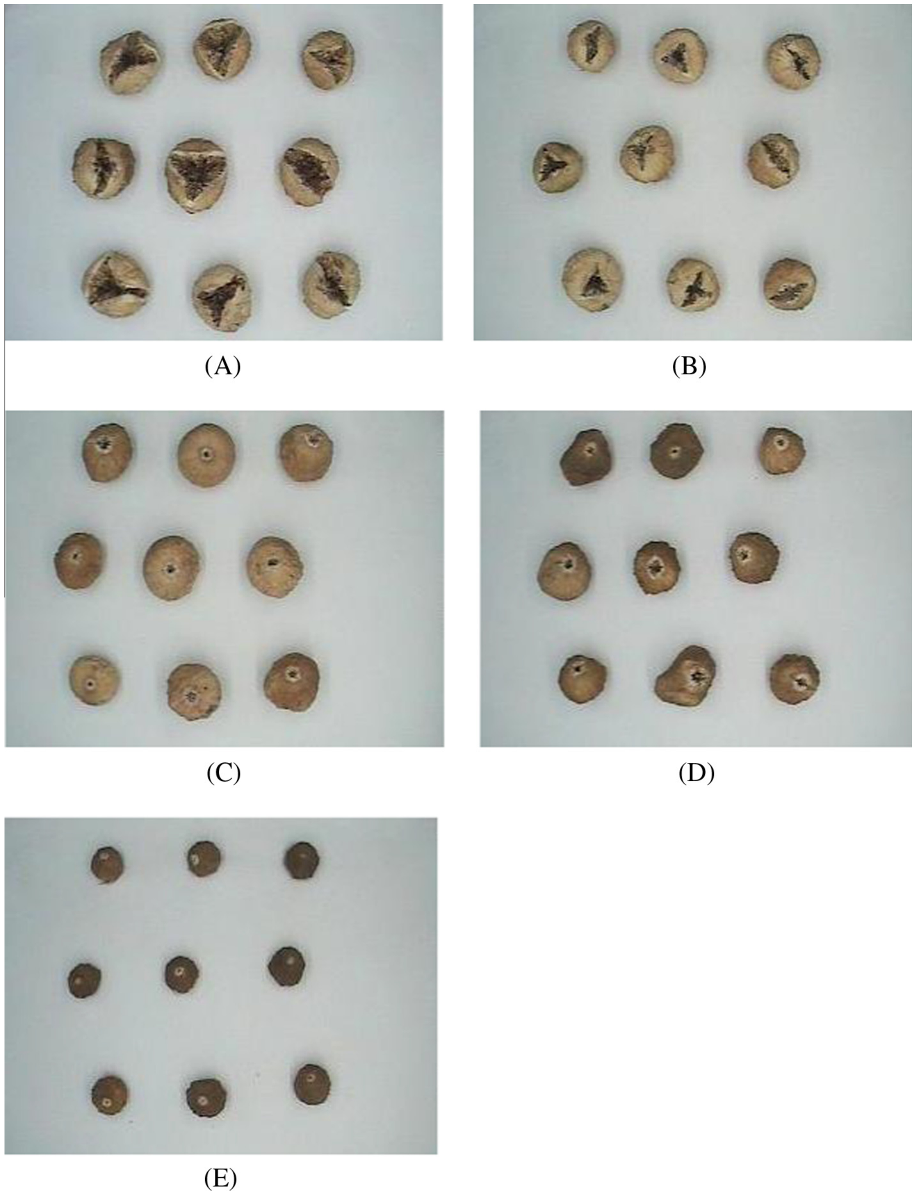

Fig. 1. The classes of figs: (A) grade 1; (B) grade 2; (C) grade 3; (D) grade 4; (E) grade 5.

When the diameter of the stimulating roller (N) is equal to 6 cm, the speed of DC motor for moving the feeder conveyor is calculated as:

$$V = N^{*}\pi D \tag{2}$$

Then, $N = \frac{V}{\pi D} = \frac{12}{3.14^{*}6} = 0.636$ cycle/s or 38.16 rpm

2.3. Machine vision section

2.3.1. Image acquisition

The machine vision system was composed of five parts of imaging box, lighting source, camera, image acquisition card, and computer. Low-level vision processing tasks need good lighting in the work environment. Hence, good and uniform illumination from an external light source is essential for machine vision applications (Kopparapu, 2006). In this research, LED lamps with white light (18 W) were used for lighting and a fiberglass sheet was mounted in front of them to produce homogenous lighting conditions. For imaging, a 750×540 pixel resolution Hi-Peak camera (HPK-6308/4) was used. The image acquisition card (Pinnacle, 510-USB Rev: 2.0) was used for transferring information from camera to computer (ACEDVio, Canopus). Moreover, a Laptop (Core-i5 CPU: 2.5 GHz; RAM: 4 GB) was used. Then, image enhancement was done for removing noises and non-homogenous lighting from the images. The main purpose of the image processing was to extract features, which was done by image processing science and MATLAB 2011 (Gonzalez and Woods, 2007). The camera was also calibrated with Hunter-lab (Hatcher et al., 2004; Leon et al., 2006).

2.3.2. Image processing algorithm

An image processing algorithm was developed in this research to extract three features of split area, equivalent diameter, and color intensity, which were used for grading the figs. The fig images were provided in the RGB space (Fig. 4(a)). In the first step, the images were smoothed in order to develop an image processing algorithm. The second stage of the image processing was image segmentation,

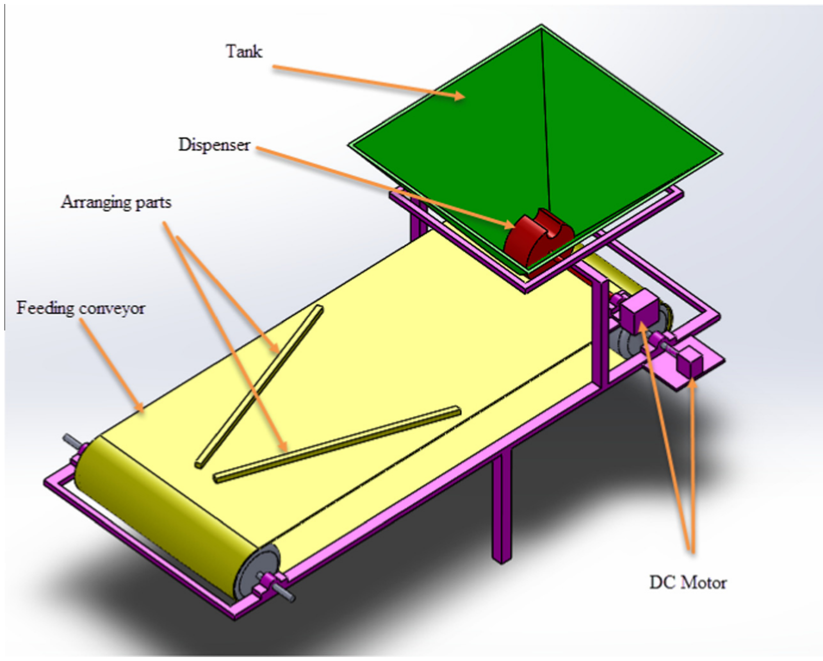

Fig. 2. Feeding unit.

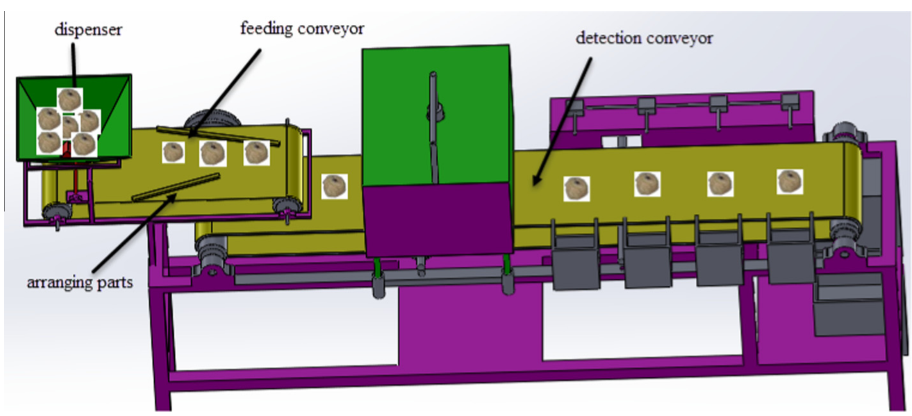

Fig. 3. Feeding conveyor.

which is probably the most important stage in ensuring the high success of any image processing algorithm (Gonzalez and Woods, 2007; Zhang et al., 2011). For segmenting objects from the background, the B channel image of the RGB image was used (Fig. 4(b)). Then, the B gray image was converted into a binary image using Otsu's histogram thresholding method, by which 1 was assigned to the object and 0 to the background. Then, erosion and dilation commands with a disc structure were used for eliminating the shadows surrounding the fruits (Fig. 4(c)) (Gonzalez and Woods, 2007). The binary image was used for calculating the area and equivalent diameter. It was also used as masking on the RGB image. The obtained image was used for calculating color features (Fig. 4(d)). For segmenting the split area for calculating its area, the region of interest (ROI) method was used. The intensity of split region's pixels in the B gray image was between 0 and 74. Based on the segmentation method, 1 was assigned to the split region pixel and 0 to the other region (Fig. 4(e)).

2.3.3. Feature extraction

Based on local experts' opinion, it was found that color, size, and amount of split were appropriate properties for grading. Therefore, in this study, the equivalent diameter as a size index, gray color intensity as a color index, and split area as a split index were extracted for the figs.

2.4. Grading unit

2.4.1. Separation unit

The separation unit was pneumatic which included electric valves with the maximum pressure of 8 bar, air nozzles, piping, fittings, and air compressor in this study. The effective length of the conveyor was 2.5 m with 30 cm width made of PVC. Conveyors were connected to a 0.75 kW electric motor by belt and pulley and their speed was adjusted by an inverter (LS, IC5, and 0.75 kW). USB data acquisition (USB-4716, Advantech Co.) was also used for the connection between computer and pneumatic operators.

2.4.2. Calculating activation delay of air nozzle

As soon as the fig images were captured, it took some times before the figs could reach in front of the air nozzle for an intended grade. Time T, was calculated by (3):

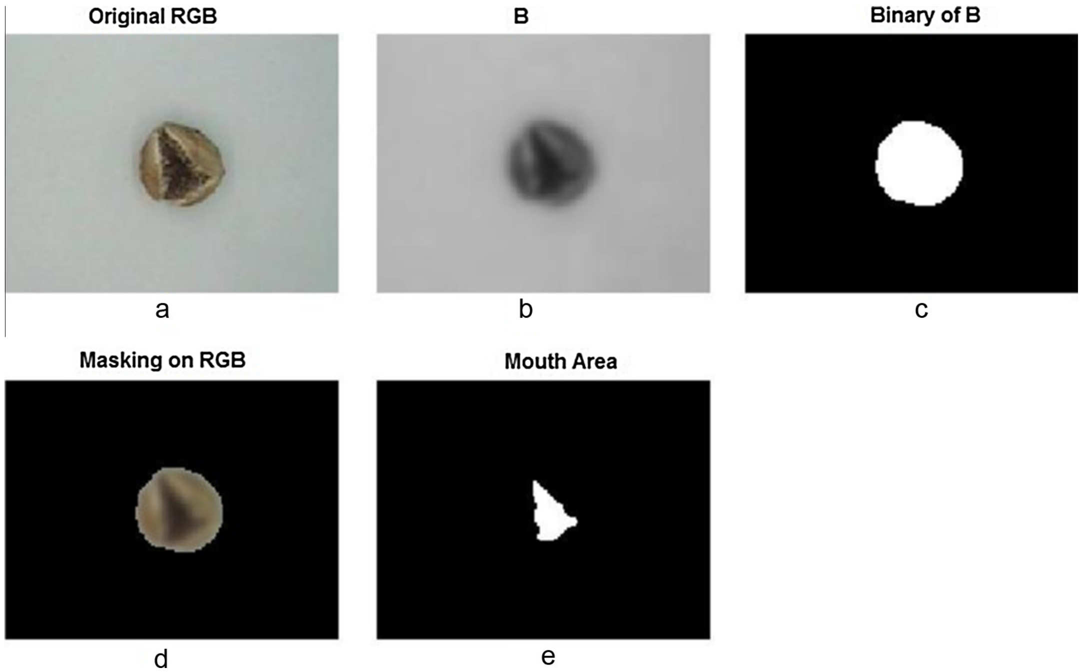

Fig. 4. (a) RGB image, (b) B gray smoothed image, (c) binary image after erosion and dilation, (d) the binary image masking on RGB image, and (e) the split area.

$$T = T_1 + T_{2i} - T_3 - T_4 \tag{3}$$

where T_1 is the required time for traveling distance X_1 between the position of an imaged fig and the end of the imaging chamber (Fig. 5). It can be calculated using the following equation, where V is the velocity of the belt conveyor

$$X_1 = V \cdot T_1 \tag{4}$$

X_1 is length of the imaging pixels minus longitudinal coordinates of the center of gravity of the fig pixels multiplied by the calibrate factor. For calibration of fig's size firstly, diameter of figs were calculated by 0.001 digital caliper. To do this, diameter of 50 figs with various sizes were measured using digital caliper carefully. Then these samples put inside lighting chamber and were photographed. The number of diameter pixels for each image were calculated. The correction factor is achieved by dividing the diameter size upon the number of pixels. Fig. 6 shows curve fitting of diameter size and the number of its pixels. The final calibrate factor is the slope of this curve. By using this function the actual diameter of figs in millimeters can be achieved from the number of diameter pixels.

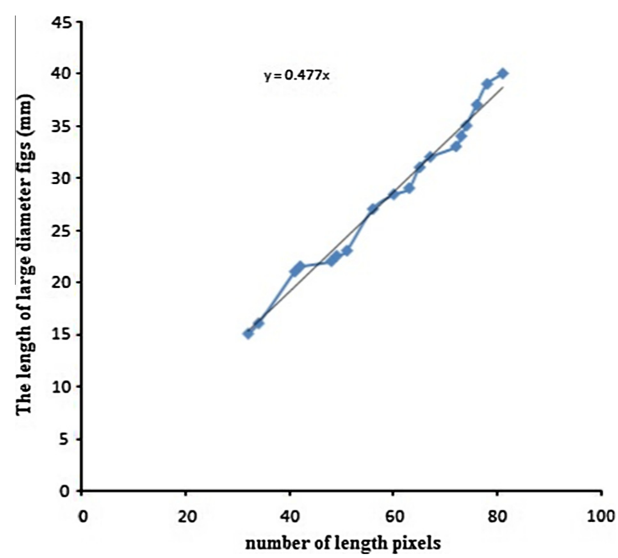

Fig. 6. Calibrate factor between diameter size and the number of its pixels.

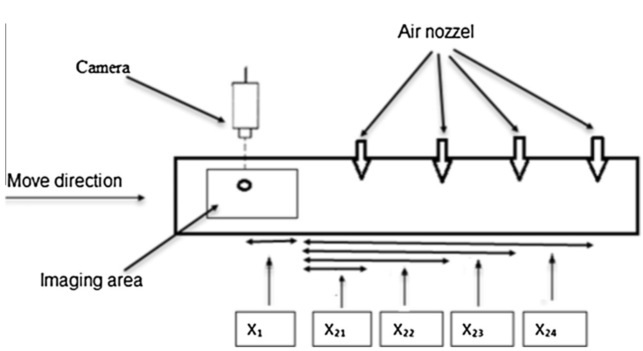

Fig. 5. Distance X_1 and X_{2i}.

T_{2i} is the required time for traveling the distance X_{2i} between the end of the imaging chamber and the air nozzle related to a desired fig grade. This time is proportional to distance X_{2i} and speed of the detection conveyor (V) (i is the detected grade of figs; 1, 2, 3, and 4):

$$X_{2i} = V^{*}T_{2i} \tag{5}$$

T_{21}: The required time for crossing the distance between the end of the imaging chamber and the front of the nozzle grade 1.
T_{22}: The required time for crossing the distance between the end of the imaging chamber and the front of the nozzle grade 2.
T_{23}: The required time for crossing the distance between the end of the imaging chamber and the front of the nozzle grade 3.

T_{24}: The required time for crossing the distance between the end of the imaging chamber and the front of the nozzle grade 4. T_3 is the required time to extract a feature from an image, and T_4 is the required time to send a command by Lab-VIEW to the DAQ card. T_3 and T_4 are different for each image and mean of T_3 and T_4 are 0.141 and 0.039 s, respectively.

2.4.3. Grading algorithm

The image processing algorithm was coupled with a grading algorithm in Lab-VIEW. Features were extracted by the image processing algorithm and, then, the fig grade was determined using the following steps designed in Lab-VIEW (Fig. 7):

1. *Grade I*: Color index of larger than 105, equivalent diameter of larger than 46 pixels (22 mm), and split area of larger than 400 pixels (96 mm^2).
2. *Grade II*: Color index of larger than 105, equivalent diameter of larger than 46 pixels (22 mm), and split area of lower than 400 pixels (96 mm^2).
3. *Grade III*: Color index of larger than 105 and the equivalent diameter of less than 46 pixels (22 mm).
4. *Grade IV*: Color index of lower than 105 and the equivalent diameter of larger than 44 pixels (22 mm).
5. *Grade V*: Color index of lower than 105 and the equivalent diameter of less than 44 pixels (22 mm).

For determining the color threshold, equivalent diameter, and split area in the grading algorithm, 50 expert-graded fig samples from each grade and their images were used. Then, the image processing algorithm was applied to extract the features which were used for determining the threshold level similar to the method used by Bato et al. (2000) for determining the respective range of values for each strawberry grade.

3. Results

The camera calibration results showed that the color, split area, and size could be measured with 98%, 96.66%, and 94% accuracy, respectively. For evaluating the precision of the image processing algorithm for measuring the split area, 50 fig samples with different split areas were selected by an expert. Based on the market studies, the figs were divided into three groups (*i.e.* fully split, semi-split, and closed) before being marketed. These samples were captured and their split areas were calculated. The results showed that the image processing algorithm managed to distinguish the split, semi-split, and closed figs with 90%, 96%, and 98% accuracy, respectively (Table 1). The difference between semi-split and fully split figs was less than the closed figs. Therefore, this algorithm was more precise in detecting the closed grade. Some of the samples from the third and fourth grades may also have small split; however, they can belong to the second grade because of their color and size values. In this paper, the B gray image was used to segment the split area. This algorithm was ambiguous in split figs, as shown in Fig. 4. This feature was only used for classifying the first class from the second class (Fig. 7). In the other classes, it was not significant.

In evaluating the precision of the image processing algorithm for measuring the size index, 50 fig samples with different equivalent diameters (large, medium, and small) were selected by an expert. The first and second grade figs were classified as "Large", third and fourth grade figs were "Medium", and fifth grade figs were "Small". These samples were imaged and their equivalent diameters were extracted. The results showed that the image processing algorithm could distinguish between large, medium, and small fig grades with 96%, 92%, and 94% accuracy, respectively (Table 2). The accuracy of the medium class was less than that of the others, because this class had some properties of both fifth and second fig grades.

For evaluating the color measurement precision of the image processing algorithm, 50 fig samples with different color values (light, semi-light, and dark) were selected by an expert. As shown in Fig. 1, most of the fourth and fifth grade figs were dark and most of the first and second grades were light. The figs belonging to the third and, partially, fourth grades, however, can be semi-light. These samples were imaged and their color intensity was calculated. The results showed that the image processing algorithm could correctly distinguish 96% of light-colored figs. The precision of semi-light figs was 98%, whereas this algorithm evaluated 100% of the dark figs (Table 3). For the purpose of separating the fourth and fifth grades from others, the color index was used.

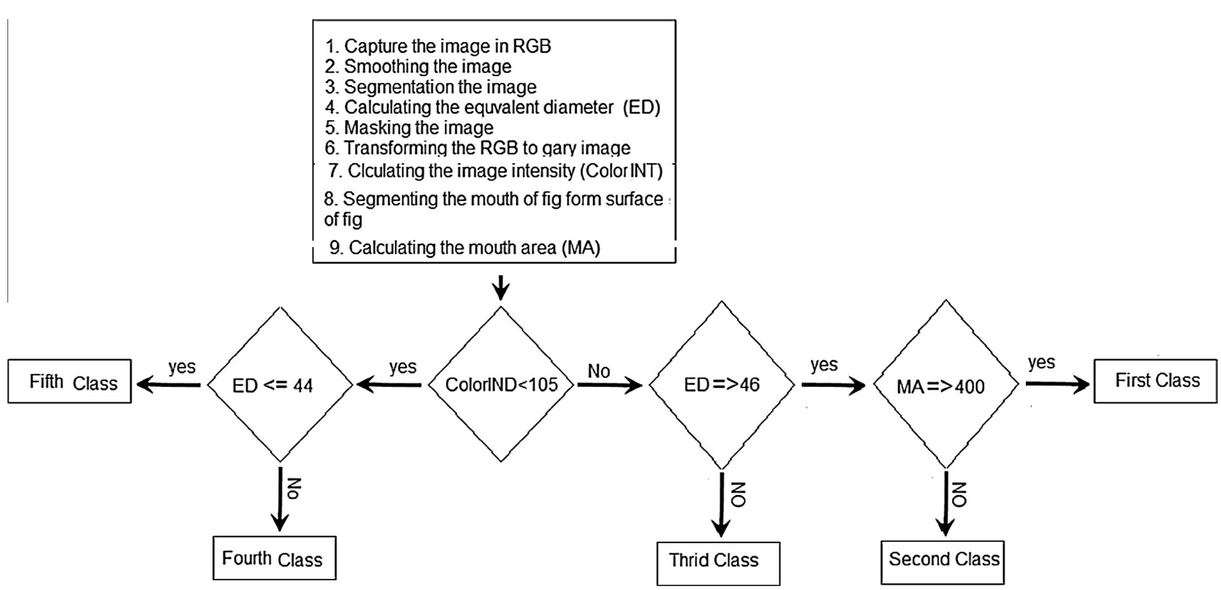

Fig. 7. Schematic of grading algorithm.

Table 1
The classification results based on mouth index.

	Opened mouth	Semi-opened mouth	Closed mouth	Num. fig	Precision
Opened mouth	45	5	0	50	90
Semi-opened mouth	1	48	1	50	96
Closed mouth	0	1	49	50	98
Total precision					96.66

Table 2
The classification results based on size index.

	Big	Medium	Small	Num. fig	Precision
Big	48	2	0	50	96
Medium	3	46	1	50	92
Small	0	3	47	50	94
Total precision					94

Table 3
The classification results based on color index.

	Light	Semi-light	Dark	Num. fig	Precision
Light	48	2	0	50	96
Semi-light	1	49	0	50	98
Dark	0	0	50	50	100
Total precision					98

Table 4
Classification results based on color, size and opened mouth index.

	G1	G2	G3	G4	G5	Num. fig	Precision
G1	45	4	1	0	0	50	90
G2	1	47	2	0	0	50	94
G3	0	1	49	0	0	50	98
G4	0	0	0	48	2	50	96
G5	0	0	0	1	49	50	98
Total precision							95.2

In summary, these results showed that the split area can be a good index for separating the first and second grade figs. The equivalent diameter can be used in the classification of the third grade and also the second and fourth grades. The best criteria for separating the fourth and fifth grades were color index. For evaluating the image processing algorithm's precision in all the five grades, 250 fig samples (50 figs per each grade) were selected by an expert, their features were extracted by the image processing algorithm, and the samples were graded by the grading algorithm using the developed grading system. The results indicated that the fig grading system graded I, II, III, IV, and V with 90%, 94%, 98%, 96%, and 98% accuracy, respectively (Table 4). The results showed that this system had a good ability for grading figs into five grades compared with the manual grading by an expert.

These results showed that four first grade figs were classified as the 2nd grade ones. Based on the grading algorithm, the split area was the index used for sorting the first grade from the second. For segmenting the split area from the background, the B gray image was employed, which had better results than other methods. Nevertheless, this method was ambiguous in the split area of figs. Therefore, some of the first-grade figs were mistakenly placed in the second grade.

Misclassification of the second grade to the third through size index had an overlap between these grades. Also, the misclassification between the fourth and fifth grades was related to the size overlap between these two classes.

After running the image processing and grading algorithm, the figs were graded. For the performance evaluation of air nozzles, 50 samples were taken from each grade. Evaluation results of the separating unit showed that its precision was 96%. The unit's error was less than 4% which can be attributed to air nozzles, delay of relays, or electrical valves. Fig. 8 shows the time taken by each section. These times were extracted by the "tic toc" function in MATLAB. The time required to extract features from an image and to send the command by Lab-VIEW to the actuator was 141 and 39 ms, respectively. Therefore, the total required time was 180 ms.

By counting the number of figs graded per hour, the system's capacity, which was 90 kg/h, was calculated. The total precision of fig grading process into 5 grades reached 95.2% by averaging the precision of each grade. It was also shown that the independent algorithm's errors for size, split, and color were less than 4%, 6%, and 2%, respectively, and the total precision was higher than 95%. Therefore, applying these machine vision systems can be easily developed into any fig grading machine. Applying this technology can be very advantageous for the fig industry and postharvest processes. Particularly, it could increase grading capacity and decrease labor and, therefore, production costs.

Benalia et al. (2013) used machine vision for grading fig fruits into three classes based on color features. Their sorting system precision was 89%, 69%, and 99.5% for the first, second, and third classes, respectively. In this study, however, the size and split features were added to the color feature for grading figs. Therefore, the classification accuracy was better than the one reported by Benalia et al. (2013). Bato et al. (2000) designed and developed sorting software with judging criteria, which could classify Akihime fig into A, B, and C classes according to shape and size. They also developed a laboratory-size belt-type sorting system. Their results showed that the sorting experiments had 98% and 100% accuracy based on shape and size judgment accuracy, respectively. The judgment time was within 1.18 s.

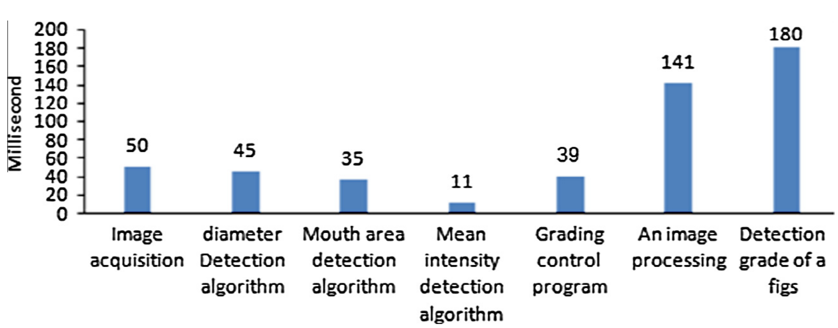

Fig. 8. Time used for every section.

4. Conclusions

The development of an inspection system that can grade figs based on marketing quality parameters would be valuable for the fig industry. In doing so, the present work tried to show that computer vision systems are useful methods to reach this objective. The results demonstrated that color, size, and split area values allowed an effective distinction between dried figs in five grades. Online sorting trials based on computer vision and visual properties also provided reliable results. It is more advantageous for the fig industry to employ postharvest processes based on this innovative technology, which allows real-time sorting, decreases processing time and labor, and thus leads to reduced production costs.

Acknowledgment

The authors would like to thank Iran National Science Foundation for their support of this project.

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