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Detecting maturity of persimmon fruit based on image processing technique

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ABSTRACT

Grading of persimmon fruits into three commercially maturity stages was conducted by image analysis technique. An automatic algorithm was developed to classify the fruits based on the external color of them. Physical, mechanical and nutritional properties of fruits were determined to compare the results of image analysis and visual classification. During the process of image segmentation, the black spots on persimmon fruits were removed to dilute the effect of them on the features to be extracted and used for classification. Among the features, there were significant differences between maturity stages for mean values of R, G, b^*, gray scale and S channels. Two classifiers based on linear (LDA) and quadratic discriminant analysis (QDA) were used to assess the applicability of vision system. The results showed that QDA classifier could be valuable in categorizing the fruits with better overall accuracy rate of 90.24%.

1. Introduction

The persimmon (*Diospyros kaki* Thunb.) as a commercially important crop is more widespread in Asian countries (Del Bubba et al., 2009). In 2011, persimmon production has been reported over than 4.3 million ton throughout the world. China with production share of 74% (3.2 million ton) is the number one producer and Korea and Japan came second and third with 9% and 4.8%, respectively (FAOSTAT, 2012). The persimmon contains bioactive compounds such as ascorbic acid, condensed tannins and carotenoids, which have many beneficial effects due to their antioxidant properties (Plaza et al., 2011). Delicate nature of persimmon, sensitive texture, poor handling applications and inadequate storage facilities have caused transportation techniques and ripening control to be very important for developing fast and new automatic systems (Luo, 2007).

Today, in various agricultural commodity grading systems, computer vision has become an alternative to visual inspection being objective, consistent, rapid, and economical (Donis-González et al., 2012). Color is the major attribute to assess quality of agricultural products more than any other single factor (Kang et al., 2008). Products color can be measured by visual, instrumental and machine vision methods (Hosseinpour et al., 2012). Accordingly, color sorting and grading have been reported as one of the best non-destructive methods, for products often have significant color changes during ripening, such as apple (Garrido-Novell et al., 2012; Leemans et al., 2002, 1999), mango (Balaban et al., 2008), peach (Lleó et al., 2011), tomato (Lana et al., 2006b), orange (Okamoto and Lee, 2009), grape (Rodríguez-Pulido et al., 2012), and cherry (Wang et al., 2012). Although firmness plays the most important role in persimmon harvesting, appearance color is usually used as a non-destructive index for harvesting (Salvador et al., 2007).

Optical sensors have been used for grading, sorting, and fruit quality detection of different crops (Abdullah et al., 2002, 2006; Conklin et al., 2002; Furferi et al., 2010; Lana et al., 2006a; Leemans et al., 1999; Pedreschi et al., 2006; Peng and Lu, 2006; Zhang et al., 2003). Blasco et al. (2008) developed a computer vision-based machine for detecting and removing unwanted material and sorting the pomegranate arils by color. Liming and Yanchao (2009) developed an automated strawberry grading system using image processing technique and graded the strawberry adopting one or two or three indices among shape, color and size. Okamoto and Lee (2009) developed an image processing method to detect green citrus fruit in individual trees to apply for crop yield estimation at a much earlier stage of growth. Furferi et al. (2010) described a method based on artificial neural network (ANN) for rapid, automatic and objective prediction of the Ripening Index of an olive lot. A multispectral machine vision was presented for grading apple fruits by minimal confusion with calyx areas on multispectral images, statistical, textural and geometric features that was

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extracted from the segmented area (Unay et al., 2011). A statistical pattern recognition technique was developed to rate objectively and consistently the quality of fresh sliced chestnuts using computer vision (Donis-González et al., 2012). In another work, oil palm fresh fruit bunch maturity was determined using a four-band sensor by acquiring reflectance data, and pattern recognition algorithms (Saeed et al., 2012). Saeed et al. (2012) used a multi-band portable, active optical sensor system, comprising of four spectral bands to detect oil palm fresh fruit bunch maturity. The potential of RGB (red, green and blue) digital imaging and hyper-spectral imaging was evaluated for discriminating maturity level of apples under different storage conditions along with the shelf-life (Garrido-Novell et al., 2012). Wang et al. (2012) reported a study of the feasibility of using computer vision to conduct accurate color rating of sweet cherry in outdoor orchard environments. Makky and Soni (2013) developed an automatic grading machine for oil palm fresh fruits bunch (FFB) based on machine-vision principles of non-destructive analytical grading, as the first automatic grading machine for FFBs in Indonesia which worked on-site. Mizushima and Lu (2013) developed an automatic adjustable algorithm for segmentation of color images, using linear support vector machine (SVM) and Otsu's thresholding method, for apple sorting and grading.

Based on the above mentioned considerations, the aim of current work is to study physical and chemical properties of persimmon fruit to develop an automated persimmon grading system using image analysis technique. Therefore, the investigation evaluates the index of external color of the fruits to classify them into three commercially maturity stages.

2. Materials and methods

2.1. Sample preparation

Persimmon fruits of the Iran variety were obtained from an orchard in the north of Iran in the mid of December 2013. The maturity index used is a visual observation of the external color of the fruit (Salvador et al., 2007). Therefore, three commercially maturity stages were accordingly defined; so, samples were classified into three groups of unripe, ripe and overripe. Just after providing samples, physical properties were evaluated and mechanical characteristics and nutritional properties were evaluated after image analysis process.

2.2. Physical properties

The geometric mean diameter D_g, equivalent diameter D_e, arithmetic diameter D_a, sphericity φ, surface area S, and aspect ratio A.R. were figured out using the following equations (Li et al., 2011):

$$D_g = (abc)^{1/3} \tag{1}$$

$$D_e = \left(\frac{a(bc)^2}{4}\right)^{1/3} \tag{2}$$

$$D_a = \frac{a+b+c}{3} \tag{3}$$

$$\varphi = \frac{(abc)^{1/3}}{a} \tag{4}$$

$$S = \pi(abc)^{2/3} \tag{5}$$

$$\text{A.R.} = \frac{\text{Major diameter}}{\text{Intermidiate diameter}} \tag{6}$$

2.3. Mechanical and nutritional properties

After image acquiring, mechanical and nutritional properties were determined. Mechanical property was firmness, and nutritional properties were total soluble solids (TSS), titratable acidity (TA) and pH of the persimmon fruits. The properties were measured for 10 samples in each group. Elasticity and firmness were determined with mechanical fruit-firmness tester Zwick (Wagner Instruments, Greenwich, CT, USA) equipped with 3 mm plunger. TSS of the specimens was measured using a manual refractometer ATAGO (ATC-1E, Japan) with a working range of 0–32 °Brix. TA was determined by titration of fruit juice with standardized 0.1 N NaOH, reaching pH 8.1 and the TA values were expressed as g malic acid per 100 ml of juice, according to A.O.A.C official method (Helrich, 1990).

2.4. Image acquisition

Image acquisition is a critical process to have high quality images and also to develop an automatic system for determining the maturity of fruits and vegetables (Hosseinpour et al., 2012). In this research, the image acquisition system had a lighting box including four LED and two fluorescent lamps (Pars Shahab Co., Tehran, Iran) positioned in the higher part of the box. Also the system had a camera (Model: PC1438, Canon Inc., Japan). The images were acquired by the system and saved in a personal computer.

2.5. Persimmon image segmentation

Once capturing was done, each image automatically was cropped using the previously written code in Matlab2008a (The Mathworks Inc., USA). Before the segmentation process, B channel obtained from the RGB image, and a filter was applied to the images to eliminate the noise. Afterwards, binary images were obtained using threshold value (0.3) for B channel. After reversing the binary image, the unwanted small objects smaller than 40 pixels were removed with erosion operation. To achieve a whole fruit image, the holes in each image were filled. Then, obtained binary images were multiplied in R, G, and B channels and by combination of them the background of the original images were removed.

Binary image were obtained using threshold value (0.3) of R channel obtained in previous step. Sometimes there are one or more visible black spots in some of persimmon fruits. In order to find them, the obtained binary image from the previous step was multiplied by R, G and B channels of original images without background. A combination of the obtained channels has been shown as the final image in Fig. 1.

2.6. Derived features from RGB images

Additional variables were calculated from the RGB values. The proportions of each of the three primary features in relation to the sum of R, G, and B (relative R, G, B) were obtained through the following formulae (Lana et al., 2006a):

$$\mathrm{R} = \frac{\mathrm{R}}{\mathrm{R+G+B}} \tag{7}$$

$$\mathrm{G} = \frac{\mathrm{R}}{\mathrm{R+G+B}} \tag{8}$$

$$\mathrm{B} = \frac{\mathrm{R}}{\mathrm{R+G+B}} \tag{9}$$

2.7. Calculations of L^* a^* b^* coordinates

The L^* a^* b^* coordinators were figured out from the RGB values as described in previous study (Mendoza and Aguilera, 2004).

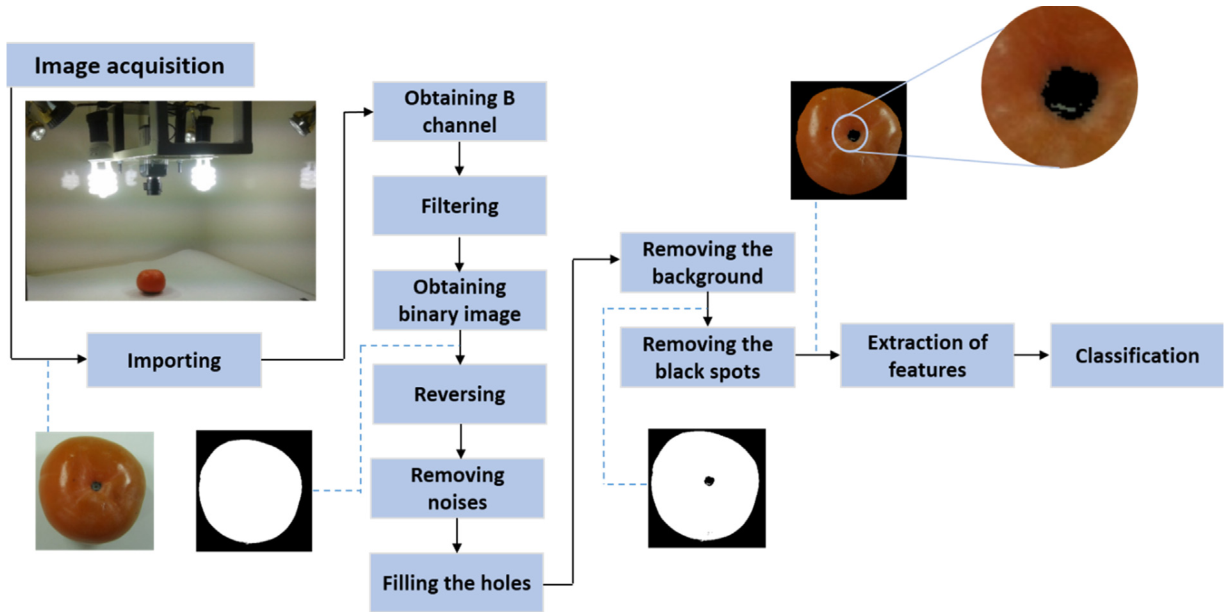

Fig. 1. The process of persimmon classification using the color categorizing algorithm.

Fig. 1 illustrates the whole image analysis process including filtering, converting, reversing, erosion, and removing black spots which they were automatically performed in batch mode using a written algorithm in Matlab software.

2.8. Standard features

For describing simple intensity information, four standard features were derived from the segmented image region for all of RGB images (Donis-González et al., 2012). These features included mean, maximum, minimum, and standard deviation.

2.9. Statistical analysis

Analysis of variance (ANOVA) was performed using SPSS software (IBM SPSS 20, USA) for the effects of maturity stages on physical, mechanical, chemical properties of fruits and extracted standard features from images, followed by Duncan multiple range test to show the significant differences between maturity levels.

2.10. Classification and validation

The ripeness level was expressed as the intensity of red color of persimmon external color. Using features extracted from persimmon images, LDA and QDA classifiers were implemented. Therefore, this last step assigns the object to a specific maturity category and states the success rate of the analytical system.

3. Results and discussion

A total of 88 persimmon images were categorized into three different ripeness classes including unripe, ripe, and overripe. As Fig. 2 illustrates approximately, a uniform distribution of images in different levels of ripeness was used for classification.

The persimmon fruits could be classified into several levels of quality in proportion to their color based on the intensity of red color in captured images. In accordance to this fact an algorithm was developed to classify the fruit. Also, there were some black spots on persimmon fruits that were removed automatically during the image analysis to dilute the effect of them on the considered features.

3.1. Physical properties

The physical and mechanical properties of persimmon fruits within three different maturity stages are shown in Table 1. These parameters are of high importance due to their relation with sensorial quality and their effects on maturity level of persimmon. The results showed that there are no significant relationship between ripeness of fruits and lengths and aspect ratio of persimmons. Also, there are slight differences between values of width and thickness, and ripeness stages. On the other hand, geometric, equivalent, and arithmetic diameters and as a result surface area and volume of overripe fruits remarkably were lower than two other stages. According to the above, physical characteristics could not be considered as useful parameters for classifying the fruits based on geometrical and shape appearance of them.

3.2. Mechanical and nutritional properties

As Table 2 gives information about mechanical properties, whatever the level of maturity increases, the elasticity and firmness of persimmon fruits decrease significantly. This effect of ripeness on mechanical properties has been reported in other studies (Salvador et al., 2007). No significant difference was found in pH values of various stages of ripeness (Table 2). As other authors have observed, just slight discrepancies of pH were observed among ripeness stages (Salvador et al., 2007). TSS increased from values

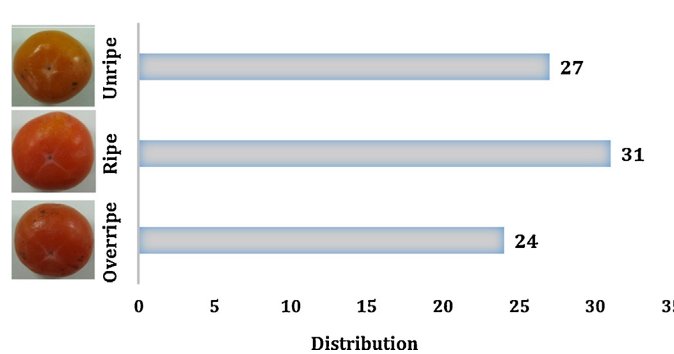

Fig. 2. Distribution of images of persimmon fruits into three maturity level.

Table 1
Physical characteristics of persimmon fruit.[a]

Characteristic	Maturity stage		
	Unripe	Ripe	Overripe
Length (mm)	64.65 ± 2.98a	64.53 ± 2.72a	63.31 ± 2.56a
Width (mm)	61.62 ± 3.31a	61.01 ± 2.92ab	59.76 ± 2.51b
Thickness (mm)	43.47 ± 1.85a	42.73 ± 2.02ab	41.36 ± 1.71b
Geometric mean diameter (mm)	55.73 ± 2.45a	55.2 ± 2.3a	53.88 ± 1.95b
Equivalent diameter (mm)	56.3 ± 2.53a	55.78 ± 2.35a	54.5 ± 2.0b
Arithmetic diameter (mm)	56.58 ± 2.541a	56.09 ± 2.35a	54.81 ± 2.02b
Sphericity (%)	86.22 ± 1.14a	85.55 ± 1.41b	85.12 ± 1.27b
Surface area (mm^2)	9776.49 ± 867.5a	9588.28 ± 797.79a	9132.83 ± 667.48b
Aspect ratio	1.05 ± 0.022a	1.058 ± 0.024a	1.06 ± 0.02a
Volume (cm^3)	112.42 ± 13.6a	112.04 ± 14.85a	104.94 ± 11.99b

[a] Values are the mean of each group of independent determinations ± standard deviation.
Different letters in the same row indicate significant differences ($p < 0.05$).

Table 2
Mechanical and nutritional properties of persimmon fruit.[a]

Characteristic	Maturity stage		
	Unripe	Ripe	Overripe
E modulus (GPs)	0.054 ± 0.012a	0.042 ± 0.005b	0.029 ± 0.004c
Firmness (N)	1.557 ± 0.48a	1.087 ± 0.24b	1.051 ± 0.24b
pH	6.21 ± 0.27a	6.16 ± 0.10a	6.31 ± 0.13a
Total soluble solid (TSS, °Brix)	17.21 ± 1.24a	19.54 ± 1.46b	21.42 ± 0.87c
Titratable acidity (%)	10.80 ± 2.39a	12.20 ± 1.48a	12.60 ± 1.52a
TSS/TA ratio	1.59 ± 0.52a	1.60 ± 0.99a	1.70 ± 0.57b

[a] Values are the mean of three independent determinations ± standard deviation.
Different letters in the same row indicate significant differences ($p < 0.05$).

Table 3
Object extracted features from persimmon images.[a]

Feature	Maturity stage		
	Unripe	Ripe	Overripe
R	0.592 ± 0.043a	0.561 ± 0.052b	0.533 ± 0.04c
G	0.228 ± 0.02a	0.204 ± 0.015b	0.188 ± 0.022c
G. scale	0.32 ± 0.019a	0.298 ± 0.019b	0.281 ± 0.23c
L^*	-62.25 ± 17.69a	-64.63 ± 16.24a	-81.86 ± 15.41b
a^*	33.93 ± 4.61a	35.45 ± 4.489a	36.29 ± 3.281a
b^*	51.41 ± 6.7a	45.65 ± 6.124b	40.29 ± 4.45c
nr	0.0026 ± 0.00058a	0.0026 ± 0.0003a	0.0028 ± 0.00038a
Ng	0.0009 ± 0.00015a	0.00088 ± 0.0001a	0.00089 ± 0.00013a
Nb	0.0003 ± 0.00036a	0.00036 ± 0.00024a	0.00039 ± 0.00025a
S	0.866 ± 0.035a	0.846 ± 0.039b	0.822 ± 0.034c

[a] Values are the mean of three independent determinations ± standard deviation.
Different letters in the same row indicate significant differences ($p < 0.05$).

of 17.21 °Brix in the unripe level to 21.42 °Brix during the maturity stages (Table 2). The results confirm the fact that during fruit development there are changes in the concentration of total soluble solids of the pulp (Wanitchang et al., 2010). Also, acidity of fruits did not have any relationship with level of ripeness.

3.3. Image analysis performance

Table 3 gives information about the results of ANOVA test used to indicate significant differences among objective features extracted from persimmon images. As the table shows, there were remarkable differences among three maturity levels for values of R, G, b^*, gray scale and S. There should be noted that differences of values of extracted features between unripe and ripe stages almost are the same difference for ripe and overripe stages. Actually, this provides a proper condition for the algorithm to classify the fruits in a higher success rate.

For automatic object classification of the fruits, two classifiers of LDA and QDA were used. Fig. 3a and b indicates the classification results of LDA and QDA in the form of confusion matrices, respectively. The numbers on the diagonal stand for correctly classified groups while off-diagonal numbers show misclassifications. In these matrices, each column denotes the occasions in a predicted category, and each row shows the instances in an actual category. These matrices are presented to document the misclassified categories (Donis-González et al., 2012). Table 4 indicates the accuracies of two mentioned methods. Accordingly, QDA classifier could classify persimmon fruits into three maturity levels with a high overall accuracy rate of 90.24%. Donis-González et al. (2012) used different classifiers including QDA, LDA, Mahalanobis distance, and support vector machine that QDA had the highest overall performance accuracy of 89.6% and 90.3% for 36 and 55 selected features, respectively.

Table 4
The results of persimmon classification.

Classifier	*R*-square	Mean square error
LDA	73.1707	0.0122
QDA	90.2439	0.0122

a	unripe	ripe	overripe
unripe	22	5	0
ripe	4	20	7
overripe	1	5	18

b	unripe	ripe	overripe
unripe	22	5	0
ripe	2	28	1
overripe	0	1	23

Fig. 3. Classification results from the discriminant analysis of the different groups. (a) LDA confusion matrix and (b) QDA confusion matrix.

Results of the current study show that the automated vision system can classify persimmon fruits into three commercially maturity levels based on external color of fruits. Although, there were no significant difference among three maturity levels of other physical features to sort fruits, QDA classifier could categorize fruits with a high accuracy based on fruits color. Therefore, the automatic algorithm could objectively, rapidly, and effectively classify persimmon fruits. So, this study proposes that a non-destructive vision technique can be used to effectively sort persimmon fruits.

4. Conclusion

The current study used image analysis technique to classify persimmon fruits into three commercially maturity stages. There were no significant differences among physical properties of fruits including main dimensions, sphericity, and volume. Therefore, sorting algorithm categorized the fruits based on the external color of persimmons. The written algorithm captured an image, eliminated the noises, obtained binary image, removed the black spots, and ultimately extracted the color features. The best result for classifying the fruits was gained by QDA classifier with a high overall accuracy rate of 90.24%. Thus, it was concluded that external color features of persimmon fruits can be potentially used to classify the fruits with a proper probability.

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References

Abdullah, M.Z., Guan, L.C., Mohamed, A., Noor, M.A., 2002. Color vision system for ripeness inspection of oil palm elaeis guineensis. J. Food Process. Preserv. 26, 213–235.
Abdullah, M.Z., Mohamad-Saleh, J., Fathinul-Syahir, A.S., Mohd-Azemi, B.M.N., 2006. Discrimination and classification of fresh-cut starfruits (*Averrhoa carambola* L.) using automated machine vision system. J. Food Eng. 76, 506–523.
Balaban, M.O., Aparicio, J., Zotarelli, M., Sims, C., 2008. Quantifying nonhomogeneous colors in agricultural materials. Part II: Comparison of machine vision and sensory panel evaluations. J. Food Sci. 73, 438–442.
Blasco, J., Aleixos, N., Cubero, S., Gómez-Sanchís, J., Moltó, E., 2008. Automatic sorting of satsuma (*Citrus unshiu*) segments using computer vision and morphological features. Comput. Electron. Agric. 66, 1–8.
Conklin, C., Watkins, R., Foo, S., Brooks, G., Roberts, R., Perry, R., 2002. Dichromatic color perception: a fast alternative for machine vision systems. Eng. Appl. Artif. Intell. 15, 351–355.
Del Bubba, M., Giordani, E., Pippucci, L., Cincinelli, A., Checchini, L., Galvan, P., 2009. Changes in tannins, ascorbic acid and sugar content in astringent persimmons during on-tree growth and ripening and in response to different postharvest treatments. J. Food Compos. Anal. 22, 668–677.
Donis-González, I.R., Guyer, D.E., Leiva-Valenzuela, G.A., Burns, J., 2012. Assessment of chestnut (*Castanea* spp.) slice quality using color images. J. Food Eng. 115, 407–414.
FAOSTAT (2012). http://faostat.fao.org (accessed 12.01.14).
Furferi, R., Governi, L., Volpe, Y., 2010. ANN-based method for olive ripening index automatic prediction. J. Food Eng. 101, 318–328.
Garrido-Novell, C., Pérez-Marin, D., Amigo, J.M., Fernández-Novales, J., Guerrero, J.E., Garrido-Varo, A., 2012. Grading and color evolution of apples using RGB and hyperspectral imaging vision cameras. J. Food Eng. 113, 281–288.
Helrich, K., 1990. Official Methods of Analysis of the AOAC International, fifteenth ed. AOAC International, Gaithersburg.
Hosseinpour, S., Rafiee, S., Mohtasebi, S.S., Aghbashlo, M., 2012. Application of computer vision technique for on-line monitoring of shrimp colour changes during drying. J. Food Eng. 115, 99–114.
Kang, S.P., East, A.R., Trujillo, F.J., 2008. Colour vision system evaluation of bicolour fruit: a case study with 'B74' mango. Postharvest Biol. Technol. 49, 77–85.
Lana, M.M., Tijskens, L.M.M., de Theije, A., Hogenkamp, M., van Kooten, O., 2006a. Assessment of changes in optical properties of fresh-cut tomato using video image analysis. Postharvest Biol. Technol. 41, 296–306.
Lana, M.M., Tijskens, L.M.M., Van Kooten, O., 2006b. Effects of storage temperature and stage of ripening on RGB colour aspects of fresh-cut tomato pericarp using video image analysis. J. Food Eng. 77, 871–879.
Leemans, V., Magein, H., Destain, M.F., 1999. Defect segmentation on 'Jonagold' apples using colour vision and a Bayesian classification method. Comput. Electron. Agric. 23, 43–53.
Leemans, V., Magein, H., Destain, M.F., 2002. AE-automation and emerging technologies: on-line fruit grading according to their external quality using machine vision. Biosyst. Eng. 83, 397–404.
Li, Z., Li, P., Liu, J., 2011. Physical and mechanical properties of tomato fruits as related to robot's harvesting. J. Food Eng. 103, 170–178.
Liming, X., Yanchao, Z., 2009. Automated strawberry grading system based on image processing. Comput. Electron. Agric. 71, S32–S39.
Lleó, L., Roger, J.-M., Herrero-Langreo, A., Diezma-Iglesias, B., Barreiro, P., 2011. Comparison of multispectral indexes extracted from hyperspectral images for the assessment of fruit ripening. J. Food Eng. 104, 612–620.
Luo, Z., 2007. Effect of 1-methylcyclopropene on ripening of postharvest persimmon (*Diospyros kaki* L.) fruit. LWT – Food Sci. Technol. 40, 285–291.
Makky, M., Soni, P., 2013. Development of an automatic grading machine for oil palm fresh fruits bunches (FFBs) based on machine vision. Comput. Electron. Agric. 93, 129–139.
Mendoza, F., Aguilera, J., 2004. Image classification of bananas (*Musa cavendish*) during ripening based on appearance features. In: Proceedings of the Ninth International Congress on Engineering and Food, Montpellier, France.
Mizushima, A., Lu, R., 2013. An image segmentation method for apple sorting and grading using support vector machine and Otsu's method. Comput. Electron. Agric. 94, 29–37.
Okamoto, H., Lee, W.S., 2009. Green citrus detection using hyperspectral imaging. Comput. Electron. Agric. 66, 201–208.
Pedreschi, F., Leon, J., Mery, D., Moyano, P., 2006. Development of a computer vision system to measure the color of potato chips. Food Res. Int. 39, 1092–1098.
Peng, Y., Lu, R., 2006. Improving apple fruit firmness predictions by effective correction of multispectral scattering images. Postharvest Biol. Technol. 41, 266–274.
Plaza, L., Colina, C., Ancos, B., Sánchez-Moreno, C., Pilar Cano, M., 2011. Influence of ripening and astringency on carotenoid content of high-pressure treated persimmon fruit (*Diospyros kaki* L.). Food Chem. 130, 591–597.
Rodríguez-Pulido, F.J., Ferrer-Gallego, R., Lourdes González-Miret, M., Rivas-Gonzalo, J.C., Escribano-Bailón, M.T., Heredia, F.J., 2012. Preliminary study to determine the phenolic maturity stage of grape seeds by computer vision. Anal. Chim. Acta 732, 78–82.
Saeed, O.M.B., Sankaran, S., Shariff, A.R.M., Shafri, H.Z.M., Ehsani, R., Alfatni, M.S., Hazir, M.H.M., 2012. Classification of oil palm fresh fruit bunches based on their

maturity using portable four-band sensor system. Comput. Electron. Agric. 82, 55–60.
Salvador, A., Arnal, L., Besada, C., Larrea, V., Quiles, A., Pérez-Munuera, I., 2007. Physiological and structural changes during ripening and deastringency treatment of persimmon fruit cv. 'Rojo Brillante'. Postharvest Biol. Technol. 46, 181–188.
Unay, D., Gosselin, B., Kleynen, O., Leemans, V., Destain, M.-F., Debeir, O., 2011. Automatic grading of Bi-colored apples by multispectral machine vision. Comput. Electron. Agric. 75, 204–212.
Wang, Q., Wang, H., Xie, L., Zhang, Q., 2012. Outdoor color rating of sweet cherries using computer vision. Comput. Electron. Agric. 87, 113–120.
Wanitchang, J., Terdwongworakul, A., Wanitchang, P., Noypitak, S., 2010. Maturity sorting index of dragon fruit: *Hylocereus polyrhizus*. J. Food Eng. 100, 409–416.
Zhang, M., De Baerdemaeker, J., Schrevens, E., 2003. Effects of different varieties and shelf storage conditions of chicory on deteriorative color changes using digital image processing and analysis. Food Res. Int. 36, 669–676.