Determination of the difference on color changes of watermelons by laser light backscattering imaging

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Abstract The potential of laser light backscattering imaging was investigated for monitoring color parameters of seeded and seedless watermelons during storage. Two watermelon cultivars were harvested and stored for 3 weeks with seven measuring storage days (0, 4, 8, 12, 15, 18, and 21). The color parameters of watermelons were monitored using the conventional colorimetric methods (L^* , a^* , b^* , C^* , H^* , and ΔE^*) and laser light backscattering imaging system. A laser diode emitting at 658 nm and 30 mW power was used as a light source to obtain the backscattering image. The backscattering images were evaluated by the extraction of backscattering parameters based on the mean pixel values. The results showed that a good color prediction was achieved by the seedless watermelon with the R^2 are all above 0.900. Thus, the application of the laser light backscattering imaging can be used for evaluating the color parameters of watermelons during the storage period.

Keywords Laser light · Backscattering imaging · Watermelon · Color changes · Storage

Introduction

Watermelon (*Citrullus lanatus*) is typically one of the valuable tropical fruit in terms of economic value. The high demand of watermelon depends solely on the fruit quality that could influence the most on purchasing fresh fruit (Sun et al. 2010). Color is the first satisfying factor that consumers opt in making decision for choosing the fresh food product (Garrido-Novell et al. 2012; Pathare et al. 2013; Zhang et al. 2014). In this case, it is important to determine the color evaluation of the agricultural produce since it could enhance the perception of the consumer. In the last decades, standard reference methods for color evaluation of watermelon were conducted using color variables. Previous studies had reported on the color measurements of watermelon in terms of CIE $L^*a^*b^*$ color space coordinates using colorimetric method (Perkins-Veazie and Collins 2004; Yau et al. 2010; Kyriacou and Soteriou 2015). Based on the colorimetric procedure, the standard method is a time-consuming process considering the fact that the color evaluation has to be repeated for the same sample. Besides, the contact measurements from certain fruit feature may also affect the result of the color evaluation (Romano et al. 2012). For this reason, the most common standard reference method with respect to color evaluation for agricultural produce is the colorimetric method. Hashim et al. (2012) investigated the kinetic model using CIE $L^*a^*b^*$ space for color evaluation of bananas during chilling injury. Similar work using CIE $L^*a^*b^*$ space was conducted by Romano et al. (2010) to determine color degradation of banana slices during drying. However, these methods are destructive and the results may produce high uncertainty if error presents during the color measurements.

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In the past few years, non-destructive techniques have shown promising applicability in monitoring the quality of various agricultural produce. Laser light backscattering imaging offers an optical-based method to evaluate quality changes in terms of mechanical, physicochemical, and physical properties of agricultural produce during storage and postharvest treatment (Mollazade et al. 2012; Adebayo et al. 2016). An advanced technique involving the use of laser light has been proven to be an accurate and rapid, to determine quality changes of horticultural products. In comparison with the colorimeter, laser light backscattering imaging system has more benefits of obtaining continuous processing of raw images on different parts of the sample without being contact to the device. The application of laser induced backscattering imaging has been evaluated on various fruit and vegetables crops such as potatoes (Babazadeh et al. 2016), citrus fruits (Lorente et al. 2015), papayas (Udomkun et al. 2014), and bananas (Hashim et al. 2013). The latest approach was established by Mohd Ali et al. (2017), to determine the firmness, soluble solids content, pH, and moisture of watermelon using the partial least squares regression analysis during storage. Another research was conducted by Rezaei Kalaj et al. (2016), to investigate the potential of laser light backscattering imaging application for evaluating variations in quality attributes of plums which related to its optical parameters during storage and the fruit development. Despite the nutritional content, quality attributes, and ripeness of watermelon, the color measurements of the fruit using laser light backscattering imaging during storage have not been discussed. Thus, the objective of this study was to develop a prediction model using partial least squares regression for online monitoring of seeded and seedless watermelons for use in a laser light backscattering imaging system.

Materials and methods

Fruit samples

Seeded (Black Beauty) and seedless (Red Seedless) watermelons were collected in late November 2015 and February 2016 from a local farm located at 4°02' north latitude and 101°18' east longitude in Perak, Malaysia. The watermelon was cultivated using a drip irrigation system on alkaline clay-loam soil with daily fertigation of 120N: 170P: 20K after transplanting for 10 days. Three replicate plots per each cultivar were applied using a completely random field experiment design. The fresh watermelons were sent to the laboratory of the Department of Agricultural and Biological Engineering, Faculty of Engineering, Universiti Putra Malaysia upon harvesting. The watermelon samples were divided into two cultivars: 70 seeded

and 70 seedless watermelons which are stored in cold storage room at 10 °C, 85% RH for 21 days. For each interval storage day, 10 watermelons from each cultivar were used for color measurements. At seven interval storage days, a total of 140 watermelon samples were used in this study.

Reference color measurements

The skin or external surface color of watermelons was measured using a handheld colorimeter (NR20XE, Shenzhen 3nh Technology Co. Ltd., China) with a measuring aperture diameter of 20 mm. The colorimeter was calibrated with a standard white tile prior taking the color measurements. The color measurements were measured for each sample by putting down the colorimeter aperture above the external surface of the sample. The aperture of colorimeter was placed upright on the watermelon surface in contemplation of minimizing the dispersion of light to the surrounding. The color measurements of each watermelon sample were performed at six locations and the average values of three replications were calculated. In addition, the total color differences (ΔE^*) was calculated between watermelon samples to determine the total color changes, which is described in Eq. (1).

$$\Delta E = \sqrt{\Delta L^{*2} + \Delta a^{*2} + \Delta b^{*2}} \quad (1)$$

Laser-induced backscattering imaging system

A laser light backscattering imaging system was developed for this study, consisting of a charge-coupled device (CCD) camera (QICAM Color Fast 1394, QImaging, Surrey, BC, Canada) with a zoom lens (F5.6 and focal length of 18 mm). A laser diode emitting at 658 nm with 1 mm diameter beam and 30 mW maximal power was applied as a light source of the CCD camera. The distance between the CCD camera and the watermelon samples was set at 55 cm, whereas the incident angle of the laser beam was placed at 22°. The backscattering images of each fruit sample comprised of 1392 × 1040 pixels by 12 bits. The image acquisition process was taken in a closed frame covered with black cloth to avoid the ambient light from the surroundings. A total of six backscattering images were captured per each fruit sample to attain the mean pixel values based on the backscattering parameters.

In order to obtain the mean pixel values of backscattering parameters, the image segmentation process was done using Matlab software (Version R2013a, The Mathworks Inc., Natick, MA, USA). The significance of image segmentation was to retrieve the region of interest (ROI) and the removal of saturated pixels of the backscattering

images. The ROI was selected after the image smoothing was carried out using Gaussian filter to remove unwanted noise in the image. The histogram profile was used to choose the threshold value to get the ROI. Based on the images, six backscattering parameters were obtained including the maximum intensity, minimum intensity, mean intensity, major axis length, minor axis length, and perimeter. Figure 1 shows the backscattering image analysis using image segmentation processes. The datasets of backscattering parameters were transferred to Unscrambler software (Version 10.3, CAMO AS, Oslo, Norway) for the development of the prediction model.

Statistical analysis

Two-way analysis of variances (ANOVA) was performed to determine the differences of storage day for each watermelon cultivar using SAS software (Version 9.4, SAS Institute, Cary, NC, USA). The differences between mean values and standard errors by 95% confidence interval were determined by Tukey test. The Pearson's correlation (r) of the color parameter was also obtained with SAS software (Version 9.4, SAS Institute, Cary, NC, USA).

Partial least squares (PLS) are one of an important bilinear regression approach for multivariate calibration, especially in the food quality analysis. PLS combined a

number of variables into a smaller number of latent variables which are known as a linear combination of backscattering parameters (X) in order to predict the quality parameters (Y). The number of latent variables is determined to avoid the over-fitting during the development of calibration model. The watermelon samples were then divided into calibration (70%) and prediction (30%) datasets. The calibration and prediction models were then developed using PLS regression using Unscrambler software (version 10.3, CAMO AS, Oslo, Norway). The coefficient of determination (R^2), root mean square error of calibration (RMSEC), and root mean square error of prediction (RMSEP) were calculated to determine the correlations between color properties and backscattering parameters. The accuracy of the PLS model was determined by the RMSEP and RMSEC, which is described in Eqs. 2 and 3, respectively.

$$\text{RMSEP} = \sqrt{\frac{\sum_{i=1}^n (\hat{y}_{pi} - y_i)^2}{2}} \quad (2)$$

$$\text{RMSEC} = \sqrt{\frac{\sum_{i=1}^n (\hat{y}_{ci} - y_i)^2}{2}} \quad (3)$$

where $\hat{y}_{pi}$ is the predicted value, $\hat{y}_{ci}$ is the calibrated value, y_i is the measured value, and n is the number of fruit samples.

Fig. 1 The backscattering image analysis using image segmentation processes: **a** raw backscattering image, **b** image smoothing using Gaussian filter, **c** histogram profile distribution of image pixel, **d** ROI of the segmented image

Results and discussion

Statistics of color measurements

The findings of the skin color measurements in both the seeded and seedless watermelons during the seven storage days are summarized in Table 1. The lightness index (L^*) gradually increased and a^* decreased along with the storage days (0, 4, 8, 12, 15, 18, and 21) in both the seeded and seedless watermelons. No significant difference was observed for L^* for seeded and seedless watermelons, which increased by 21% and 12% at day 4, respectively. As for the a^* values, there was no significant difference in both the seeded and seedless watermelons. The trend of a^* values which represent the redness index was quite similar for both types of the cultivar. Previous research also reported that the a^* values did not greatly affect the redness of the watermelons (Feng et al. 2013). Meanwhile, the b^* values increased along with the storage day for both types of the cultivar. Nevertheless, there was no significant difference reported for the seeded watermelon for the b^* values. The variation from the L^* , a^* , and b^* values of the seeded and seedless watermelons was perhaps due to the different textures that affect the firmness changes on the external surface or skin color of the fruit.

On the other hand, the results exhibited an increase in the chroma (C^*) values for the seedless watermelon with a significant difference at day 21. Moreover, there was no significant difference in the C^* value changes for the seeded watermelon. The C^* values revealed only slight changes with no clear trend noticed along with the storage days. Similar results were reported by Ibarra-Garza et al. (2015) who indicated that the decline in the C^* values could probably reflect the absence of lightness and a minor discrepancy in hue tones of the surface of the fruit. However, the hue (H^*) values did not exhibit a variation over the storage days for both the seeded and seedless watermelons. As observed in the findings, there was no significant difference for the seeded watermelon as the color changes were similar throughout the storage days. Since there was a variation in the color parameters of the seedless watermelon, it could be implied that color evaluation is a feasible method to observe the color changes through the ripening process of the fruit. The color total differences (ΔE^*) in CIE $L^*a^*b^*$ is the distance between the location of color in the CIE color space. Previous studies have been investigated the ΔE^* in the measurement of color changes in various fruit crops such as strawberries (Fernández-Lara et al. 2015), grapefruits (Igual et al. 2014), and pineapples (Chutintrasri and Noomhorm 2007). In this study, the overall ΔE^* of both seeded and seedless watermelons

increased from 21.70 to 27.31 and 24.65 to 32.45, respectively. An overview of calibration and prediction sets of seeded and seedless watermelons is presented in Table 2. In this study, 70 samples from both seeded and seedless watermelons were divided into the calibration and prediction set (70:30).

Selection of backscattering parameters

To establish an online laser light backscattering imaging system, some important feature extraction reflecting the backscattering parameters for predicting color parameters were selected. The F-values (ANOVA) of backscattering parameters in the color evaluation of watermelons were calculated to obtain the significant effect of the experimental factors (storage day and type of cultivar), and their interactions at $P < 0.05$ (Table 3). The postharvest storage days were evaluated based on the cultivars of the watermelons which were influenced by the changes in the backscattering parameters. Based on the results, significant differences were observed for all backscattering parameters of watermelons, except for the maximum intensity when subjected to different storage day. The major axis length revealed the highest F-values (9.22) whereas the maximum intensity did not have a significant effect on all the backscattering parameters in terms of storage day. Meanwhile, the mean intensity and minimum intensity showed the highest (66.98) and the lowest (8.74) F-values, respectively based on the type of cultivar. The mean intensity showed the highest significant changes at $P < 0.05$ with the F-value of 16.48 for the interaction of storage day and type of cultivar. Mohd Ali et al. (2017) reported that the backscattering parameters influenced the interaction between the storage day and type of cultivar on the firmness, soluble solids content, pH, and moisture of the watermelon. The effect of postharvest storage on the physicochemical properties of the seeded and seedless watermelons was studied in the present study, considering the classification of the watermelon samples according to the type of cultivars and different storage days.

Development of color prediction models

PLS is a powerful linear regression method for multivariate calibration that is commonly used to predict quality attributes of food products (Rady et al. 2015). The optimal number of latent variables (LV) was obtained by the smallest value of predicted residual error sum of squares in order to remove random errors in the data sets. PLS models were developed for predicting color parameters of watermelons non-destructively after removing the outliers from the calibration and prediction datasets (Table 4). Both the

Table 1 The color parameters of seeded and seedless watermelons at different storage days

Day	Seeded						Seedless					
	L*	a*	b*	C*	H*	ΔE^*	L*	a*	b*	C*	H*	ΔE^*
0	24.08 ± 3.35 ^a	-4.32 ± 2.30 ^a	11.52 ± 3.39 ^a	12.41 ± 3.68 ^a	104.55 ± 2.11 ^a	21.70 ± 2.14 ^a	35.32 ± 3.91 ^a	-7.26 ± 0.76 ^a	20.23 ± 3.19 ^a	22.17 ± 3.43 ^a	106.30 ± 1.80 ^a	24.65 ± 3.89 ^a
4	29.35 ± 0.37 ^b	-5.19 ± 1.28 ^{ab}	15.07 ± 2.12 ^{ab}	16.09 ± 2.26 ^{ab}	107.22 ± 0.33 ^b	22.43 ± 3.34 ^a	39.56 ± 0.79 ^b	-8.99 ± 0.37 ^b	24.88 ± 0.58 ^b	27.32 ± 0.92 ^b	109.74 ± 0.42 ^{ab}	25.87 ± 2.53 ^a
8	31.19 ± 1.14 ^c	-5.34 ± 1.06 ^{ab}	17.83 ± 3.54 ^{ab}	18.86 ± 3.57 ^{ab}	108.54 ± 0.20 ^{bc}	23.65 ± 2.19 ^{ab}	41.47 ± 0.36 ^{bc}	-10.00 ± 0.21 ^c	27.37 ± 0.59 ^{bc}	30.04 ± 0.47 ^{bc}	111.40 ± 0.65 ^b	26.94 ± 3.11 ^{ab}
12	33.01 ± 0.52 ^{cd}	-5.49 ± 1.42 ^{ab}	18.67 ± 2.28 ^b	19.70 ± 2.32 ^b	109.53 ± 0.31 ^{cd}	23.92 ± 3.43 ^b	43.19 ± 0.66 ^{cd}	-10.74 ± 0.32 ^d	28.84 ± 0.35 ^{cd}	31.37 ± 0.42 ^{cd}	112.73 ± 0.32 ^{bc}	28.85 ± 3.65 ^b
15	34.82 ± 1.04 ^{de}	-5.13 ± 2.44 ^{ab}	18.06 ± 2.45 ^b	19.18 ± 2.59 ^b	110.45 ± 0.28 ^d	24.58 ± 2.08 ^a	45.16 ± 0.65 ^{de}	-11.73 ± 0.24 ^e	30.07 ± 0.47 ^d	32.48 ± 0.59 ^d	113.76 ± 0.32 ^{cd}	29.52 ± 2.41 ^a
18	38.41 ± 1.28 ^e	-5.53 ± 2.06 ^{ab}	19.39 ± 3.41 ^{bc}	20.45 ± 3.59 ^{bc}	111.70 ± 0.60 ^e	25.87 ± 3.65 ^c	47.38 ± 1.09 ^e	-12.29 ± 0.10 ^e	32.12 ± 0.66 ^e	34.57 ± 0.64 ^e	114.53 ± 0.26 ^d	31.88 ± 3.83 ^c
21	43.28 ± 1.70 ^f	-7.45 ± 1.93 ^b	23.11 ± 5.41 ^c	24.49 ± 5.75 ^c	113.77 ± 0.94 ^f	27.31 ± 2.54 ^c	51.06 ± 1.35 ^f	-13.06 ± 0.53 ^f	36.84 ± 2.57 ^f	38.95 ± 2.45 ^f	116.60 ± 3.48 ^e	32.45 ± 2.79 ^c

Data represents the mean and three replicates ($\pm$ standard error). Different letters within the same column indicate statistical difference by the Tukey's test, $P < 0.05$ and stored for 0, 4, 8, 12, 15, 18, and 21 days

calibration and prediction PLS models showed a good performance with a high value of R^2 and low RMSEP values for each color parameter. From the table, the a^* color parameter showed the best physicochemical properties to be predicted by the backscattering parameters from the samples for seeded and seedless watermelons, respectively. The prediction models of seedless watermelon in terms of L^* , a^* , and b^* are shown in Fig. 2.

The calibration and prediction models based on the backscattering parameters of both watermelon cultivars were used to predict the L^* value. For the L^* prediction of seeded watermelon, the calibration gave $R^2 = 0.864$ and RMSEC = 1.440, whereas the prediction obtained $R^2 = 0.761$ and RMSEP = 1.500. Meanwhile, the calibration gave $R^2 = 0.913$ and RMSEC = 1.092, whereas the prediction obtained $R^2 = 0.903$ and RMSEP = 0.728 for seedless watermelon, respectively. The results of correlation analysis showed that the L^* value correlated with the highest correlation with the backscattering parameter, specifically with the seeded watermelon. Additionally, the correlation of L^* value with backscattering parameter for seedless watermelon also obtained high correlation, especially with the pixel intensity measurements (mean intensity, maximum intensity, and minimum intensity). Udomkun et al. (2014) mentioned that illuminated area and light intensity parameters exhibited the best prediction values with the $r = 0.915$ for the prediction of L^* during papaya drying. Nevertheless, the PLS models indicated that the pixel intensity values from laser-induced backscattering were the most significant feature among all correlated to the color parameters.

The calibration and prediction models based on the backscattering parameters of both watermelon cultivars were used to predict the a^* value. For the a^* prediction of seeded watermelon, the calibration gave $R^2 = 0.306$ and RMSEC = 1.439, whereas the prediction obtained $R^2 = 0.271$ and RMSEP = 1.868. Meanwhile, the calibration gave $R^2 = 0.979$ and RMSEC = 0.220, whereas the prediction obtained $R^2 = 0.965$ and RMSEP = 0.103 for seedless watermelon, respectively. The a^* value obtained the lowest prediction for seeded watermelon. However, the prediction of a^* value for seedless watermelon obtained the highest correlation with the backscattering parameters. According to Romano et al. (2012), there is no significant correlation between the colorimeter data of a^* value and the scattering area as well as light intensity during bell pepper drying at 532 and 635 nm. The differences of a^* prediction between the seeded and seedless watermelons were possibly due to the larger area obtained from the backscattering images. Therefore, the propagation of photon in the fruit tissue was decreased during postharvest storage, indicating that the discrepancy

Table 2 Summary statistics of calibration and prediction sets of seeded and seedless watermelons

Cultivar	Color parameter	N	Calibration set	Prediction set	Mean	SD	Min	Max
Seeded	L*	70	47	23	33.45	6.03	18.14	45.81
	a*	70	47	23	−5.49	1.98	−11.91	−0.15
	b*	70	47	23	17.66	4.68	6.38	30.51
	C	70	47	23	18.74	4.89	6.90	33.00
	h	70	47	23	109.39	2.95	100.20	115.37
Seedless	L*	70	47	23	43.31	5.10	25.62	53.65
	a*	70	47	23	−10.58	1.92	−14.14	−5.87
	b*	70	47	23	28.62	5.17	15.01	40.91
	C	70	47	23	30.99	5.23	16.59	42.80
	h	70	47	23	112.15	3.48	102.94	126.40

Table 3 F-values (ANOVA) of backscattering parameters in color evaluation of watermelons

Factor	Major axis length	Minor axis length	Mean intensity	Maximum intensity	Minimum intensity	Perimeter
Day	9.22*	3.29*	6.10*	2.71 ^{ns}	2.40*	6.56*
Cultivar	54.05*	39.48*	66.98*	13.43*	8.74*	29.06*
Day* CULTIVAR	8.09*	2.15*	16.48*	4.98*	3.76*	5.23*

^{ns} Non-significant* Significant at $P < 0.05$ **Table 4** Calibration and prediction models based on the backscattering parameters of seeded and seedless watermelons

Cultivar	Parameter	Calibration		Prediction	
		R ²	RMSEC	R ²	RMSEP
Seeded	L*	0.864	1.440	0.761	1.500
	a*	0.306	1.439	0.271	1.868
	b*	0.680	2.144	0.674	2.519
	C*	0.666	2.277	0.558	3.124
	H*	0.866	0.811	0.758	0.674
	ΔE*	0.743	1.547	0.698	1.768
Seedless	L*	0.913	1.092	0.903	0.728
	a*	0.979	0.220	0.965	0.103
	b*	0.941	0.899	0.912	0.906
	C*	0.931	1.039	0.900	0.904
	H*	0.967	0.494	0.949	0.152
	ΔE*	0.943	0.879	0.942	0.284

R² coefficient of determination

RMSEC root mean square error of calibration, RMSEP root mean square error of prediction

amount of light scattering when reacted to the absorption of green color of the outer surface of the watermelon.

The calibration and prediction models based on the backscattering parameters of both watermelon cultivars were used to predict the b* value. For the b* prediction of

seeded watermelon, the calibration gave $R^2 = 0.680$ and $RMSEC = 2.144$, whereas the prediction obtained $R^2 = 0.674$ and $RMSEP = 2.519$. Meanwhile, the calibration gave $R^2 = 0.941$ and $RMSEC = 0.899$, whereas the prediction obtained $R^2 = 0.912$ and $RMSEP = 0.906$ for seedless watermelon, respectively. From the findings, the b* value gave a good prediction since both the seeded and seedless watermelons achieved the correlation coefficient above 0.80. The measurement of b* value with respect to the backscattering parameters, a significant factor of the parameters, especially pixel intensity measurements was determined to evaluate the surface defect or green color surface of the watermelon. The color changes of watermelon as affected by the fruit maturity are ultimately related to the chemical and biochemical reactions during storage. The existence of green pigment including chlorophyll subjected to the degradation of enzymatic or non-enzymatic reactions when associated with the color changes of agricultural produce (Bonazzi and Dumoulin 2011).

The calibration and prediction models based on the backscattering parameters of both watermelon cultivars were used to predict the C* value. For the C* prediction of seeded watermelon, the calibration gave $R^2 = 0.666$ and $RMSEC = 2.277$, whereas the prediction obtained $R^2 = 0.558$ and $RMSEP = 3.124$. Meanwhile, the calibration gave $R^2 = 0.931$ and $RMSEC = 1.039$, whereas the prediction obtained $R^2 = 0.900$ and $RMSEP = 0.904$

Fig. 2 Prediction models of seedless watermelon: **a** L^* , **b** a^* , and **c** b^* values

for seedless watermelon, respectively. Based on the C^* prediction model, the C^* value correlated best with the backscattering parameters. However, the light absorption of the seeded and seedless watermelons during storage might influence the pigmentation of C^* value since the minimal degradation occurred during the storage period. The results from the prediction model based on the light intensity parameters (mean intensity, minimum intensity,

maximum intensity), also described the most important feature, in which the backscattering parameters correlated with the chroma value.

The calibration and prediction models based on the backscattering parameters of both watermelon cultivars were used to predict the H^* value. For the H^* prediction of seeded watermelon, the calibration gave $R^2 = 0.866$ and $RMSEC = 0.811$, whereas the prediction obtained $R^2 = 0.758$ and $RMSEP = 0.674$. Meanwhile, the calibration gave $R^2 = 0.967$ and $RMSEC = 0.494$, whereas the prediction obtained $R^2 = 0.949$ and $RMSEP = 0.152$ for seedless watermelon, respectively. Based on the findings, the H^* value also gave a good prediction since both the seeded and seedless watermelons achieved the correlation coefficient above 0.80. The correlation analysis between H^* value and backscattering parameters, especially light intensity measurements (mean intensity, minimum intensity, and maximum intensity) described the most important feature among the backscattering parameters. On the other hand, the calibration gave $R^2 = 0.743$ and $RMSEC = 1.547$, whereas the prediction obtained $R^2 = 0.698$ and $RMSEP = 1.768$ for the ΔE^* prediction of seeded watermelon. The calibration gave $R^2 = 0.943$ and $RMSEC = 0.879$, whereas the prediction obtained $R^2 = 0.942$ and $RMSEP = 0.284$ for seedless watermelon, respectively. Based on this prediction, results showed that the seedless watermelon can be visually differentiated from the seeded watermelon in terms of colorimetric variables since the ΔE^* prediction gave higher prediction values than the seeded cultivar.

Conclusion

In this work, the change of backscattering parameters was evaluated using a laser light backscattering system for online monitoring of watermelons during storage. The results showed that the color prediction (L^* , a^* , b^* , C^* , H^* , and ΔE^*) gave the highest R^2 with all of them above 0.9 for seedless watermelon, respectively. The backscattering parameters which are selected based on the feature extraction can provide a foundation for the development of a reliable laser light backscattering imaging system for online quality control measurements of watermelons. A laser light backscattering imaging system would be helpful for real-time inspection of other food quality parameters if it can be improved under industry standard requirements. Therefore, this study has demonstrated the capability of laser light backscattering imaging as a useful, rapid, and non-invasive optical technique for the color evaluation of the quality of watermelons during postharvest storage.

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References

- Adebayo SE, Hashim N, Abdan K, Hanafi M (2016) Application and potential of backscattering imaging techniques in agricultural and food processing—a review. *J Food Eng* 169:155–164
- Babazadeh S, Ahmadi Moghaddam P, Sabatyan A, Sharifian F (2016) Classification of potato tubers based on solanine toxicant using laser-induced light backscattering imaging. *Comput Electron Agric* 129:1–8
- Bonazzi C, Dumoulin E (2011) Quality changes in food materials as influenced by drying processes. Wiley-VCH Verlag GmbH & Co. KGaA, Weinheim
- Chutintrasri B, Noomhorm A (2007) Color degradation kinetics of pineapple puree during thermal processing. *LWT Food Sci Technol* 40:300–306
- Feng M, Ghafoor K, Seo B et al (2013) Effects of ultraviolet-C treatment in Teflon-coil on microbial populations and physico-chemical characteristics of watermelon juice. *Innov Food Sci Emerg Technol* 19:133–139
- Fernández-Lara R, Gordillo B, Rodríguez-Pulido FJ et al (2015) Assessment of the differences in the phenolic composition and color characteristics of new strawberry (*Fragaria* × *ananassa* Duch.) cultivars by HPLC-MS and imaging Tristimulus colorimetry. *Food Res Int* 76:645–653
- Garrido-Novell C, Pérez-Marin D, Amigo JM et al (2012) Grading and color evolution of apples using RGB and hyperspectral imaging vision cameras. *J Food Eng* 113:281–288
- Hashim N, Janius RB, Baranyai L et al (2012) Kinetic model for colour changes in bananas during the appearance of chilling injury symptoms. *Food Bioprocess Technol* 5:2952–2963
- Hashim N, Pflanz M, Regen C et al (2013) An approach for monitoring the chilling injury appearance in bananas by means of backscattering imaging. *J Food Eng* 116:28–36
- Ibarra-Garza IP, Ramos-Parra PA, Hernández-Brenes C, Jacobo-Velázquez DA (2015) Effects of postharvest ripening on the nutraceutical and physicochemical properties of mango (*Mangifera indica* L. cv Keitt). *Postharvest Biol Technol* 103:45–54
- Igual M, Contreras C, Martínez-Navarrete N (2014) Colour and rheological properties of non-conventional grapefruit jams: instrumental and sensory measurement. *LWT Food Sci Technol* 56:200–206
- Kyriacou MC, Soteriou G (2015) Quality and postharvest performance of watermelon fruit in response to grafting on interspecific cucurbit rootstocks. *J Food Qual* 38:21–29
- Liu C, Liu W, Chen W et al (2015) Feasibility in multispectral imaging for predicting the content of bioactive compounds in intact tomato fruit. *Food Chem* 173:482–488
- Lorente D, Zude M, Idler C et al (2015) Laser-light backscattering imaging for early decay detection in citrus fruit using both a statistical and a physical model. *J Food Eng* 154:76–85
- Mohd Ali M, Hashim N, Bejo SK, Shamsudin R (2017) Quality evaluation of watermelon using laser-induced backscattering imaging during storage. *Postharvest Biol Technol* 123:51–59
- Mollazade K, Omid M, Tab FA, Mohtasebi SS (2012) Principles and applications of light backscattering imaging in quality evaluation of agro-food products: a review. *Food Bioprocess Technol* 5:1465–1485
- Pathare PB, Opara UL, Al-Said FAJ (2013) Colour measurement and analysis in fresh and processed foods: a review. *Food Bioprocess Technol* 6:36–60
- Perkins-Veazie P, Collins JK (2004) Flesh quality and lycopene stability of fresh-cut watermelon. *Postharvest Biol Technol* 31:159–166
- Rady A, Guyer D, Lu R (2015) Evaluation of sugar content of potatoes using hyperspectral imaging. *Food Bioprocess Technol* 8:995–1010
- Rezaei Kalaj Y, Mollazade K, Herppich W et al (2016) Changes of backscattering imaging parameter during plum fruit development on the tree and during storage. *Sci Hortic (Amsterdam)* 202:63–69
- Romano G, Argyropoulos D, Gottschalk K et al (2010) Influence of colour changes and moisture content during banana drying on laser backscattering. *Int J Agric Biol Eng* 3:46–51
- Romano G, Argyropoulos D, Nagle M et al (2012) Combination of digital images and laser light to predict moisture content and color of bell pepper simultaneously during drying. *J Food Eng* 109:438–448
- Sun T, Huang K, Xu H, Ying Y (2010) Research advances in nondestructive determination of internal quality in watermelon/melon: a review. *J Food Eng* 100:569–577
- Udomkun P, Nagle M, Mahayothee B, Müller J (2014) Laser-based imaging system for non-invasive monitoring of quality changes of papaya during drying. *Food Control* 42:225–233
- Yau EW, Rosnah S, Noraziah M et al (2010) Physico-chemical compositions of the red seedless watermelons (*Citrullus Lanatus*). *Int Food Res J* 17:327–334
- Zhang B, Huang W, Li J et al (2014) Principles, developments and applications of computer vision for external quality inspection of fruits and vegetables: a review. *Food Res Int* 62:326–343