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Research Article

Determine the color change of fresh green lettuce by using reflectance reconstruction from RGB image

Suwan Aekram[1]*, Wittaya Prompuge[1], Piyapong Wongkhunkaew[1], Bunyarit Samosor[1], Worakrit Doncomephang[1], Noppadol Treerat[1], Boonjerd Kanjan[1]

[1] *Faculty of Science and Agricultural Technology, Rajamangala University of Technology Lanna Phitsanulok, 65000, Thailand*

[*] *Corresponding author: aekrum@gmail.com*

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Abstract-This paper presents an image processing technique to determine the color change of salad lettuce is stored at 15ºC for storage times of 0 to 5 days. The technique divided the color of salad lettuce into 8 clusters (Dark-green, Light-green, Green-yellow, Brown, Dark, White, Shadow, and background) and used these clusters for spatial and spectral analysis. In the case of spatial analysis, the number of pixels of each cluster was countering over storage time for calculating the area of each cluster in the image and was used to determine the color change of the lettuce salad. In cases of spectral analysis, the reflectance reconstruction technique was applied to reconstruct the reflectance data from the image. RGB values from these images were transformed to tri-stimulus values (XYZ) and *L*a*b** and then used with a trust-region-dogleg algorithm for reconstruction the reflectance from *L*a*b** values. The reflectance data were normalized by an average sum of reflectance and called relative reflectance, and then use in the partial relative reflectance in a range of blue (450-500 nm), green (500-570 nm), and red (610-650 nm) to calculate the spectral gradient. The spectral gradient was used to determine the color change of the lettuce salad over storage. The result of both spatial and spectral analysis shows that changes in the colors of lettuce can be detected at storage time in days 3.

Keywords: Lettuce, image processing, reconstruction, color change

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1. Introduction

In recent years, the consumption of fresh-cut produce has been increasing due to changes in the lifestyles of consumers. For example, lettuce (*Lactuca sativa L.*) has an annual production value of $3.5 billion in the United States (U.S. Department of Agriculture, 2020), with 24.7 lb of lettuce consumed per capita (U.S. Department of Agriculture, 2019). However, processing of the products promotes faster quality change, especially color. For this reason, most fresh-cut products are sold within a few weeks after packaging. Because the consumers usually purchase fresh-cut produce based on their visual appearance, color is an extremely important factor in consumer purchasing selection. (Martinez *et al*., 2021; Kader, 2013; Ferrante *et al*., 2004).

Color is the first parameter of quality evaluation of food products by consumers, and it is critical in the acceptance or rejection of the product (Du & Sun, 2004; Pedreschi *et al*., 2006). To determine the color of food products, visual inspection or color measuring with instruments can be carried out. The visual inspection is a subjective technique. The accuracy of this technique depends upon the observer. To objectively determine more information, such as objective color, color standards are often used as reference material. However, this technique is quite slow and requires more specialized training of the observers (Gnanasekharan *et al*., 1992). Therefore, the determination of color for more information should be performed via a color measuring instrument.

Colorimeters are electronic devices for color measurement that express colors in numerical coordinates. These devices are commonly used in the laboratory and industry to measure color. However, colorimeters are limited to the measurement of small regions in which the object has a homogeneous color (Gardner, 2007). To go beyond this limit, a new technique, namely image processing has been widely used for objectively measuring the color of various food products. This technique provides some advantages over a conventional colorimeter such as it can be used to determine color on a larger region, heterogeneous surfaces, and provides the possibility for analyses of the entire surface of the food (Brosnan & Sun, 2004). This may be extended via imaging with a measurement device.

In the image, each pixel is characterized by three components (red, green and blue, RGB) which can be registered as any color observed by humans. So, the color of many foods can be measured by image processing (Saldaña, 2013; Blasco *et al*., 2009; Mendoza & Aguilera, 2004). However, the color from images is illumination dependent, when changing the illumination, and the color of the images is changed. To solve this problem, reconstruction reflectance has been an interesting avenue of exploration. Due to the reflectance is an illumination independent property of the object. Obtaining the reflectance data from the RGB image could provide a new way of using digital cameras in spectroscopy (Dejana *et al*., 2015). The reflectance data are recognized as the "fingerprint" of an object's surface and provide the most fundamental information (Zhang & Xu, 2009). It can be used to identify biochemical properties of the object and/or determine the quality change in the products (Lu *et al*., 2019). Therefore, in this paper, we present the methods used to determine the color changes of fresh-cut produce by using fresh green loose-leaf Lettuce (*Lactuca Sativa L.*) as the sample base for reflectance data. This was recovered from RGB images. In this method, all pixels in the images were reconstructed. For this reason, the quality changes can be analyzed on both spectral and spatial data in the images.

2. Materials and methods

2.1 Sample preparation

Fresh green Loose-leaf lettuces (*Lactuca sativa L.)* have a shelf life of 42 days before harvest was purchased in the morning from a local hydroponic vegetable farm, then washed in cold (8°C), chlorinated (100 ppm) water for 30 s, shredded and centrifuged in a salad spinner for 1 minute to remove excess water. The shredded lettuces were packed in 10 (7 inch × 11 inch) LDPE bags of 40 g each. To accelerate the degradation of the lettuce samples, the lettuce samples were stored at 15°C under atmospheric conditions.

2.2 Image acquisition system

The image acquisition system consists of a wood box whose internal walls were painted white to avoid the light and reflection of the room, two fluorescent lights using for illumination (Philips, natural daylight, 18W, length 30 cm, color temperature of 6500 K). The lamps were arranged 30 cm above the samples, at an angle of 45°to the sample plane to give a uniform light intensity over the samples. A digital camera (Nikon D7200) was used for capturing images. The camera was in a vertical position at 25 cm from the samples and at an angle of 45° from the light source. The image was captured at a resolution of 1200×900 pixels, storage in the RGB color model and JPEG format. The images were captured every 24 h for 5 days.

2.3 Color transformation

Since the RGB color model is device dependent, it was decided to solve this problem using color transformation. In agricultural and food products, the $L^*a^*b^*$ color model has been widely used due to this model relating to human perception. The L^* parameter is an attribute by which a surface emits reflected light and can take values between 0 (absolute black) to 100 (absolute white). The parameters a^* and b^* represent the chromaticity and can take values between -120 to 120, a^* defines the red-green component (red for positive values and green for negative values) and the b^* parameter defines the yellow-blue component (yellow for positive values and blue for negative values) (León *et al*., 2006). Transformation of values in RGB to $L^*a^*b^*$ involves two steps of conversion. In the first step the RGB color model was converted to tri-stimulus values (XYZ) by following (1)-(4) (Poynton, 1996).

$$r = \begin{cases} (((R/255) + 0.055)/1.005)^{2.4}, R/255 > 0.04045 \\ (R/255)/12.92, R/255 \leq 0.04045 \end{cases} \quad (1)$$

$$g = \begin{cases} (((G/255) + 0.055)/1.005)^{2.4}, G/255 > 0.04045 \\ (G/255)/12.92, G/255 \leq 0.04045 \end{cases} \quad (2)$$

$$b = \begin{cases} (((B/255) + 0.055)/1.005)^{2.4}, B/255 > 0.04045 \\ (B/255)/12.92, B/255 \leq 0.04045 \end{cases} \quad (3)$$

Subsequently the rgb values to XYZ using the matrix M for a D65-2° illuminate-observer (4) (Blasco *et al*., 2007).

$$\begin{bmatrix} X \\ Y \\ Z \end{bmatrix} = 100 \times \begin{bmatrix} 0.4124564 & 0.3575761 & 0.1804375 \\ 0.2126729 & 0.7151522 & 0.0721750 \\ 0.0193339 & 0.1191920 & 0.9503041 \end{bmatrix} \times \begin{bmatrix} r \\ g \\ b \end{bmatrix} \quad (4)$$

Second step, involving the conversion of XYZ to *L*a*b**, this step can be implemented by following (5)-(10).

$$x = \frac{X}{Xn} \quad (5)$$

$$y = \frac{Y}{Yn} \quad (6)$$

$$z = \frac{Z}{Zn} \quad (7)$$

Where *Xn*, *Yn* and *Zn* are tri-stimulus values obtained by the weighted-ordinate method. For D65 lamp and 2° *Xn* = 95.047, *Yn* = 100.000 and *Zn* = 108.883 respectively.

Subsequently the *xyz* into equation, for compute $f\left(X/_{Xn}\right), f\left(Y/_{Yn}\right)$ and $f\left(Z/_{Zn}\right)$, respectively.

$$f\left(X/_{Xn}\right) = \begin{cases} 7.787x + 16/116, x \le 0.008856 \\ x^{1/3}, x > 0.008856 \end{cases} \quad (8)$$

$$f\left(Y/_{Yn}\right) = \begin{cases} 7.787y + 16/116, y \le 0.008856 \\ y^{1/3}, y > 0.008856 \end{cases} \quad (9)$$

$$f\left(Z/_{Zn}\right) = \begin{cases} 7.787z + 16/116, z \le 0.008856 \\ z^{1/3}, z > 0.008856 \end{cases} \quad (10)$$

Subsequently $f\left(X/_{Xn}\right), f\left(Y/_{Yn}\right)$ and $f\left(Z/_{Zn}\right)$ into (11)-(13) for calculating *L*a*b**, respectively.

$$L^* = 116 f\left(Y/_{Yn}\right) - 16 \quad (11)$$

$$a^* = 500\left[f\left(X/_{Xn}\right) - f\left(Y/_{Yn}\right)\right] \quad (12)$$

$$b^* = 200\left[f\left(Y/_{Yn}\right) - f\left(Z/_{Zn}\right)\right] \quad (13)$$

2.4 Color calibration

To calibrate the color from the images, 1269 chips of Munsell color books were measured by a spectrophotometer (HunterLab, ColorQuest XE, Hunter Associates Laboratory, Inc., USA) with three replicates and record *L*a*b** values. The same Munsell chips were captured by an image acquisition system and compared to color from an image with a spectrophotometer. This mean normalized error was used for determining the error of comparing of each of the parameters (*L*, a** and *b**). Statistical analysis was achieved by MS Excel at a confidence level of 95%.

2.5 Reconstruction reflectance from the image

The CIEXYZ tri-stimulus value can be calculated from (14) to (17), when $R(\lambda)$ is spectral reflectance, $S(\lambda)$ is the relative spectral power of a CIE standard illuminate and $\bar{x}(\lambda), \bar{y}(\lambda), \bar{z}(\lambda)$ are color matching function of one of the CIE standard observer.

$$X = k\int R(\lambda)S(\lambda)\bar{x}(\lambda)d\lambda \quad (14)$$

$$Y = k\int R(\lambda)S(\lambda)\bar{y}(\lambda)d\lambda \quad (15)$$

$$Z = k\int R(\lambda)S(\lambda)\bar{z}(\lambda)d\lambda \tag{16}$$

Where,

$$k = 100 / \int R(\lambda)S(\lambda)\bar{y}(\lambda)d\lambda \tag{17}$$

In practical, continuous functions ((14) to (16)) can be sampled to discrete functions (for example 5 or 10 nm intervals) without any significant loss of accuracy. In this paper, spectral reflectance was sampled in the range of 400-700 nm at 10 nm intervals. Then, (14) to (16) can be written as.

$$X = \sum_{400}^{700} W_x R(\lambda)\Delta\lambda \tag{18}$$

$$Y = \sum_{400}^{700} W_y R(\lambda)\Delta\lambda \tag{19}$$

$$Z = \sum_{400}^{700} W_z R(\lambda)\Delta\lambda \tag{20}$$

Where W_x, W_y and W_z are weighting factor obtained from inner product of relative spectral power of standard illuminate $S(\lambda)$, the color matching function of standard observer ($\bar{x}(\lambda), \bar{y}(\lambda), \bar{z}(\lambda)$) and normalizing factor k. For given tri-stimulus values, the spectral reflectance $R(\lambda)$ can be reconstructed. In the same way, $L^*a^*b^*$ values which widely to use in agricultural and food products can be used to reconstruct reflectance ($R(\lambda)$) by subsequently XYZ from (18) to (20) into (11) to (13). Then, (11) to (13) can be written as below.

$$L^* = 116 f\left(\frac{\sum_{400}^{700} W_y R(\lambda)\Delta\lambda}{Yn}\right) - 16 \tag{21}$$

$$a^* = 500\left[f\left(\frac{\sum_{400}^{700} W_x R(\lambda)\Delta\lambda}{Xn}\right) - f\left(\frac{\sum_{400}^{700} W_y R(\lambda)\Delta\lambda}{Yn}\right)\right] \tag{22}$$

$$b^* = 200\left[f\left(\frac{\sum_{400}^{700} W_y R(\lambda)\Delta\lambda}{Yn}\right) - f\left(\frac{\sum_{400}^{700} W_z R(\lambda)\Delta\lambda}{Zn}\right)\right] \tag{23}$$

In this paper, reflectance spectra of each pixel were reconstructed by using trust-region-dogleg algorithm and use the spectral data from the Munsell database for the initial value to solve the nonlinear system of Equations ((21)-(23)). For more accuracy, we used the solution value from the previous step as the initial value to solve (21)-(23) again.

2.6 Validation of reflectance reconstruction

To validate the reflectance reconstruction, 1269 chips of Munsell color books were measured by a spectrophotometer (HunterLab, ColorQuest XE, Hunter Associates Laboratory, Inc., USA) with three replicates to record spectra of each chip and the same chips were captured by the image acquisition system and reconstructed reflectance. The reflectance from the spectrophotometer and reconstructed ware compared and Good Fitting Curve (GFC) was used to determine the best fit.

2.7 Determination of the color change of vegetable

To apply image processing as color perceiving for indication of the remaining usable life of fresh vegetable products, the technique must be capable of accurately computing the difference between the original color region and the new color region formed during the storage time. Since the pixel based RGB value is transformable to the surface reflectance value, the derivative of surface reflectance with respect to wavelength implies indeed the rate of change of an RGB value. However, interpretation of vegetable quality using a quite large image of the actual product size based on the direct comparison of the pixel-based surface reflectance values required very long computation time.

We propose a method to determine the color change in an area of lettuce salad. This method can determine both spatial and spectral data. In spatial cases, we divided color of lettuce into 8 classes (Dark-green, Light-green, Green-yellow, Brown, Dark, White, Shadow and background). Then clustering all pixels in the image into each class by using k-mean clustering. The number of pixels in each class over storage time was used to determine the area of each cluster in the image and used to determine the change of color in the image. In spectral case, the average spectra of each cluster over storage time were calculated and used to determine the spectral gradient.

Before investigating spectral gradient, it should be known that a photometric feature is constructed from image irradiance represented as.

$$I(\mathbf{x},\lambda)=g(\mathbf{x})e(\mathbf{x},\lambda)s(\mathbf{x},\lambda) \tag{24}$$

Where $g(x)$ is the geometric factor, $e(x, \lambda)$ is the incident illumination, $s(x, \lambda)$ is the diffuse surface reflectance of the object, all projected to $x = (x, y)$ in the image plane, and λ represents wavelength direction of visible light spectral (Berwick & Lee, 2004). The image irradiance given in Equation (24) includes confounded effects of geometry, illumination, and surface reflectance and it can take the logarithm to separate the multiplicative terms into additive terms as below.

$$\begin{aligned} L(\mathbf{x},\lambda) &= \ln I(\mathbf{x},\lambda) = \ln g(\mathbf{x}) + \ln e(\mathbf{x},\lambda) + \ln s(\mathbf{x},\lambda) \\ &= G(\mathbf{x}) + \varepsilon(\mathbf{x},\lambda) + S(\mathbf{x},\lambda) \end{aligned} \tag{25}$$

In this paper, we assumed that the effects of geometry and illumination are constant for all images. Because all images were captured in the same environment, therefore, different color in the image is caused by only surface reflectance. For this reason, we can calculate the *spectral gradient* or gradient of $L(x, \lambda)$ as only effects of surface reflectance in λ direction as shown below.

$$L_\lambda(\mathbf{x},\lambda)=\frac{\partial L(\mathbf{x},\lambda)}{\lambda}=\frac{\partial S_\lambda(\mathbf{x},\lambda)}{S(\mathbf{x},\lambda)}=S_\lambda \tag{26}$$

Even though the effects of geometry and illumination are negligible to image irradiance, the pixel based reflectance intensity of each color image is greatly different due to the color perceiving principle. Therefore, they cannot be applied directly to indicate a degree of color changing of the image. In this paper, before calculating the spectral gradient from Equation (26), we normalize the reflectance by the average sum of reflectance and called relative reflectance and use the partial relative reflectance in a range of blue (450-500 nm), green (500-570 nm) and red (610-650 nm) to calculate the spectral gradient (Equation 27) then use it to determine color gradient (Equation 28), this method applies to all clusters. The results of this method can indicate that the color has changed from the original. Additionally, we investigate the ratio between spectral and spatial gradients. This ratio can be indicative that changes in the spectral gradient is how much pixel changes have occurred. This result can be useful to carry out the reflectance spectral from spectrophotometer and use it to predict the change of pixel area equivalent to use of image analysis.

$$\begin{bmatrix} \frac{dRed}{d\lambda} \\ \frac{dGreen}{d\lambda} \\ \frac{dBlue}{d\lambda} \end{bmatrix} = \begin{bmatrix} 3.2405 & -1.5371 & -0.4983 \\ -0.9693 & 1.8760 & 0.0416 \\ 0.5560 & -0.0240 & 1.0572 \end{bmatrix} \begin{bmatrix} \frac{dX}{d\lambda} \\ \frac{dY}{d\lambda} \\ \frac{dZ}{d\lambda} \end{bmatrix} \quad (27)$$

Where $\frac{dX}{d\lambda}, \frac{dY}{d\lambda}, \frac{dX}{d\lambda}$ are slope of XYZ value with wavelength (λ) from Fourier fitting.

$$\frac{dColor}{d\lambda} = 256^2 \frac{dRed}{d\lambda} + 256 \frac{dGreen}{d\lambda} + \frac{dBlue}{d\lambda} \quad (28)$$

3. Results and discussion

3.1 Color calibration

The $L^*a^*b^*$ values from spectrophotometer and images of 1269 Munsell chips were compared. The results show that the average error of colors was below ±5% (L^* = ±4. 82%, a^* = ±3.97%, b^* = ±4.00%) which is acceptable (Gutiérrez-Pulido & Salazar, 2004). In addition, the Orthogonal Regression of $L^*a^*b^*$ values between the spectrophotometer and image processing data shown in (Figure 1) bears this point out. We found that the R^2 is higher than 0.95 which indicates that colors from both techniques are similar ($P>0.05$). From these results, we confirmed the image processing can be used for measuring the color variance.

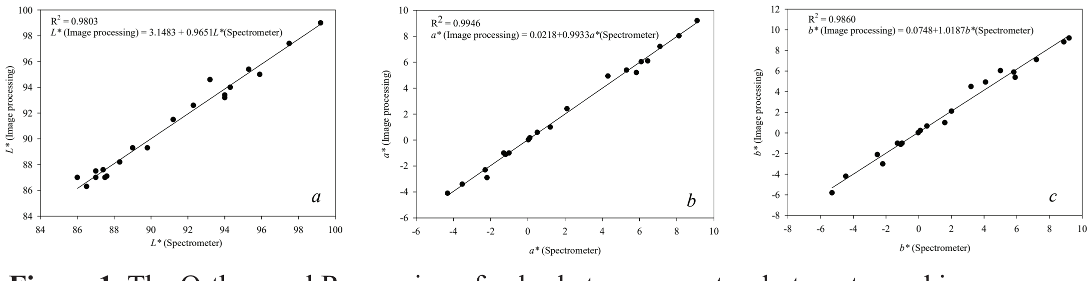

Figure 1. The Orthogonal Regression of color between spectrophotometer and image processing: (a) L^*, (b) a^* and (c) b^*.

3.2 Validation of reflectance reconstruction

The reflectance spectral of some Munsell chips from the spectrophotometer and reconstruction was compared and are shown in (Figure 2). This paper uses the average $L^*a^*b^*$ values of all pixels in Munsell chip images to reconstruct the reflectance spectrum. The results show that the reflectance spectra of many spectral lines of both techniques is similar. Consider the results in (Figure 2), we show many spectral lines of Munsell chips (7.5GY8/8, 2.5YR6/4, 5Y8.5/12, 7.6RP5/12). The code-named chips 7.5GY8/8 are dominant in the green zone, which is the main color in lettuce. The code-named chips 2.5YR6/4 and 5Y 8.5/12 represent the brown and yellow zones, which refer to poor quality of lettuce. The spectrum of all code names is reconstructed like the spectrophotometer with GFC > 0.95 this confirmed that the reflectance from reconstructed data has more accuracy, especially, in the main colors of lettuce. In addition, (Figure 2) shows the spectral line of 7.5RP 5/12, which is dominant in the red-pink zone which does not occur in lettuce. But the spectral line from spectrophotometer and image processing is similar (GFC>0.9).

The spectral lines of several colors were carried out from spectrophotometer and reconstruction and showed show good fitting. To be confirmed, the spectra must produce the true color. We tried to render images from the reconstructed reflectance with the relative spectral power of a CIE standard illuminate and color matching function of D65-2° (illuminate-observer at 10 nm intervals) of the lettuce images and the results are shown in (Figure 3). In this case, rendering of the image rather than like the original image. For this reason, we confirm that the color change of lettuce can be determined from reconstructed reflectance.

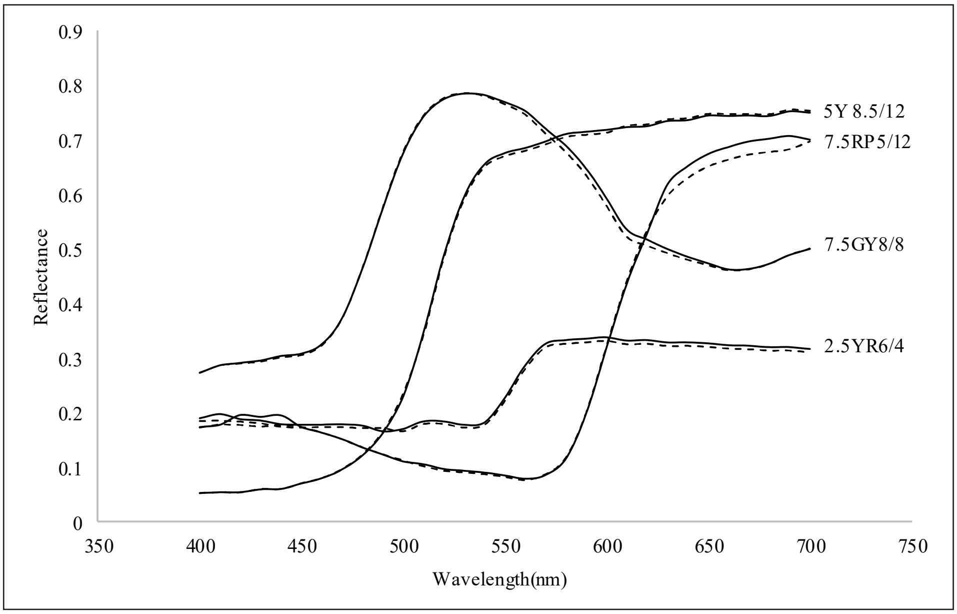

Figure 2. Reflectance spectral from spectrophotometer (——) and reconstruction (-----)

Figure 3. (*a*) Lettuce image from camera and (*b*) rendering image from reflectance reconstruction

3.3 Determine the color change of lettuce salad

In this paper, we use both spatial and spectral data to determine the color changes of salad lettuce. In the spatial case, the number of pixels of each cluster was counted and showed in Figure 4. The results show that the green cluster decreased over storage time while light-green clusters increased from days0 to days3, green-yellow cluster increased from days0 to days4 then decreased until the final storage time (days5), brown and dark cluster increased over storage time. These results indicate that there are changes of color in all main clusters over storage time.

Although, this proposed method can detect changes of color in each cluster, it cannot indicate whether there are any changes from any cluster to any other cluster. However, it can monitor color change in overall image or interest cluster. In addition, it can also indicate the amount of color change in each cluster. For example, in the brown cluster, which is the one of most colors that were used to monitor the quality change of fruit and vegetable. Results showed that it is increasing the pixel area from 0.48% at storage time at day0 to 11.14% at day 4. At the same time, we found that other clusters of changes of color are such as the brown clusters. The color change increased to 31.79% of the sample area of light-green cluster and 7.41% of the green-yellow within 3 days of storage. These results are like those obtained in a similar study that investigated the quality change of fresh-cut produce by image analysis (Lunadei *et al*., 2012; Zhou, 2004). They found that in samples stored at 4°C -10°C, the area of color changes amnifests at around 10% of the sample area. It can be detected by the consumer. This is the most significant change in color which occurred within the first 4-6 days of storage. In this study, we found that consumers can detect the color change of lettuce within 3 days of storage time if it was stored at temperature is higher than 10°C (Figure 4).

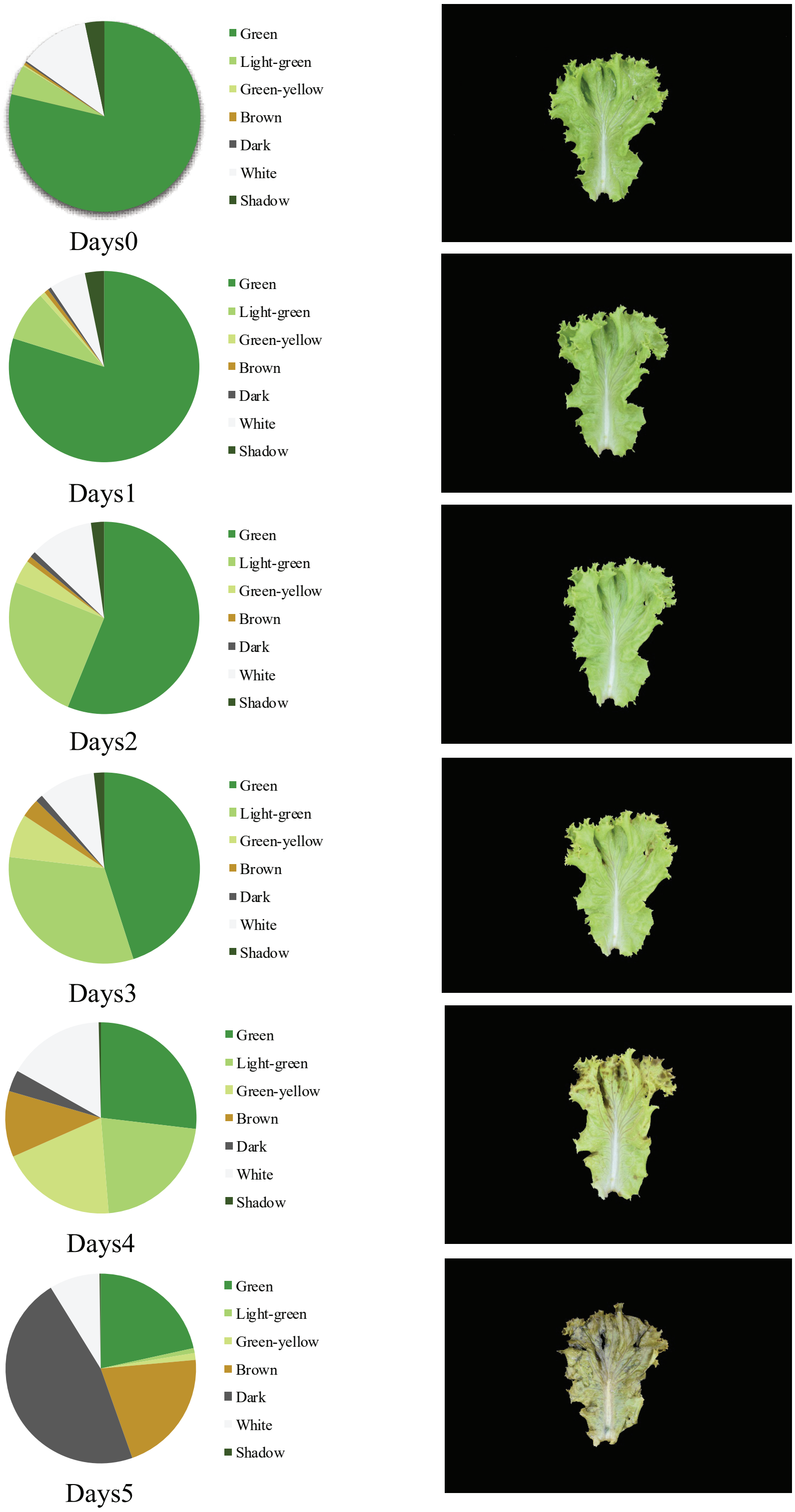

Figure 3. (*a*) Lettuce image from camera and (*b*) rendering image from reflectance reconstruction

In spectral case, the spectral gradient was calculated and used to calculate the color gradient. (Figure 5) shows the color gradient per number of pixels (CGP) of green clusters, light-green color and green-yellow with storage time, respectively. In cases of green clusters, the color gradient per number of pixels with storage times of 0-3 days, rather than decreasing, constantly, due to the color of lettuce samples in this case, was slightly changed which differs from storage time of 4-5 days. In storage times of 4 and 5 days the color of lettuce was changed from green to brown and dark. For light-green and green-yellow clusters, CGP increases in a range of storage times from 0-3 days, which indicates that the lettuce tended toward light and yellow with longer storage times. For storage times of 4-5 days, the CGP of green, light-green and green-yellow clusters were highly decreased due to the color change to brown and dark. According to the findings of this study, the critical point at which consumers can detect a change in the color of lettuce is 3 days, which is consistent with the findings of Aekrum and Lertsiriyothin (2015), who used image texture properties to analyze the quality of green oak vegetables. Green oak vegetables stored at 15°C have been found to have severe changes in surface quality after 4 days or more. In addition, (Table 1) and (Table 2) show the percentages of difference of dColor/dλ and pixel area of Green, Light-green, Green-yellow, Brown and Dark clusters are represented comparing data of storage times at days0. The results show that, Brown and dark clusters have more difference in dColor/dλ but slight differences in the pixel area, but in the contrast to Green in the pixel areas, but in contrast to Green, Light-green and Green-yellow clusters. These results tell that, for the large area clusters (Green and Light-green clusters) on the first day of storage, the slight changes in dColor/dλ resulted in a significant change in the area. But, for Brown and Dark clusters, in which small areas in the first day of storage changed in small areas and requires more change in dColor/dλ. Therefore, color change considerations should be focused on some cluster that indicate the change in productivity.

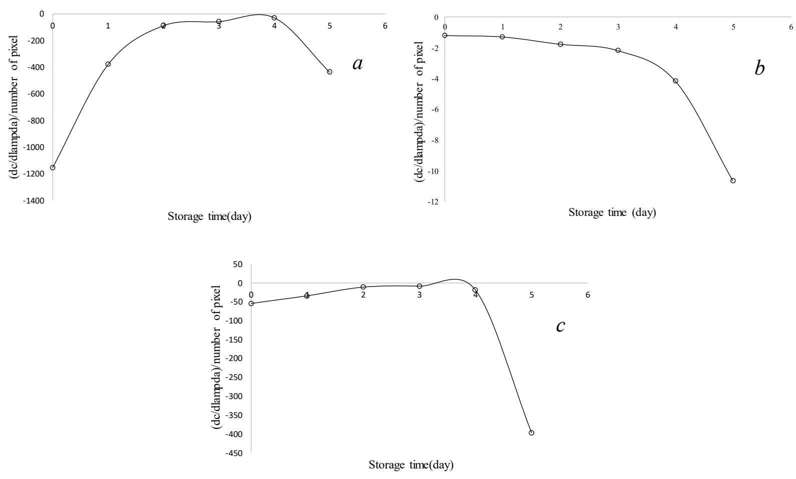

Figure 5. The color gradient per number of pixels of green (A), light-green (B) and yellow green (C) cluster respectively.

Table 1. Show the percentage difference in dColor/dλ and pixel area of Green, Light-green, Green-yellow clusters comparing with data of storage time at days0.

Storage time (days)	Cluster					
	Green		Light-green		Green-yellow	
	Δ(dColor/dλ) (%)	Δ(area) (%)	Δ(dColor/dλ) (%)	Δ(area) (%)	Δ(dColor/dλ) (%)	Δ(area) (%)
1	4.86	-1.34	2.51	3.27	-9.41	0.56
2	5.30	-22.09	-0.66	20.29	-2.09	3.81
3	2.93	-33.68	1.81	27.33	14.40	7.25
4	6.42	-54.62	36.74	15.25	28.21	18.05
5	104.48	-60.86	2.80	-4.41	19.50	0.68

Table 2. Show the percentage difference in dColor/dλ and pixel area of Brown and Dark clusters comparing with data of storage time at days0.

Storage time (days)	Cluster			
	Brown		Dark	
	Δ(dColor/dλ) (%)	Δ(area) (%)	Δ(dColor/dλ) (%)	Δ(area) (%)
1	46.60	0.26	122.59	0.34
2	60.12	0.48	244.50	0.79
3	300.40	2.77	282.10	1.04
4	457.39	9.91	625.17	3.15
5	-64.23	17.90	-90.87	40.41

4. Conclusion

This paper proposes a method to use image processing to determine color changes of fresh-cut produce, which use salad lettuce as the sample. The proposed method of using both spatial and spectral data to determine the color change. The spectral of all pixels was reconstructed by using a trust-region-dogleg algorithm and clustering spectrum into 8 clusters then a countering number of pixels for each cluster. The results show that, the percentage area of the main clusters (green, light-green, green-yellow, brown and dark) were changed over storage time and it can be indicated that the critical storage time within which a consumer can detect the color change of produce for this result is 3 days of storage time, within which the area change around 10% from the original. In addition, the spectral data also calculated the color gradient per number of pixels. The results can be used to indicate the critical storage time, which is like using the percentage area.

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6. References

Aekrum, S., & Lertsiriyothin, W. (2015). Evaluation of quality changes of green oak salad using image texture analysis. *Agricultural Science Journal, 46*(Suppl.), 421-424.

Berwick, D., & Lee S.W. (2004). Spectral gradients for color-based object recognition and indexing. *Computer Vision and Image Understanding, 7*(1-3), 28-43.

Blasco, J., Aleixos, N., Cubero, S., Juste, F., Gómez-Sanchís, J., Alegre, V., & Moltó, E. (2009). Computer vision developments for the automatic inspection of fresh and processed fruits. *Image Analysis for Agricultural Processes and Products*, 21-34.

Blasco, J., Cubero, S., Arias, R., Gómez, J., Juste, F., Moltó, E. (2007). Development of a Computer Vision System for the Automatic Quality Grading of Mandarin Segments. In J. Martí, J.M. Benedí, A.M. Mendonça, & J. Serrat (eds), *Pattern Recognition and Image Analysis* (pp. 460-466). Springer.

Brosnan, T., & Sun, D.W. (2004). Improving quality inspection of food products by computer vision. *Food Engineering Reviews, 61*(1), 3-16.

Dejana, J., Tim, J., & Andrej, J. (2015). Comparison of two digital cameras based on spectral data estimation obtained with two methods. *Acta Polytechnica Hungarica, 12*(7), 183-197.

Du, C., & Sun, D.W. (2004). Recent developments in the applications of image processing techniques for food quality evaluation. *Trends in Food Science & Technology, 15*, 230-249.

Ferrante, A., Vernieri, P., Serra, G., & Tognoni, F. (2004). Changes in abscisic acid during leaf yellowing of cut stock flowers. *Plant Growth Regulation, 43*, 127-134.

Gardner, J. L. (2007). Comparison of calibration methods for tristimulus colorimeters. *Journal of Research of the National Institute of Standards and Technology, 112*(3), 129 -138.

Gnanasekharan,V., Shewfelt, R. L., & Chinnan M.S. (1992). Detection of color changes in green vegetables. *Journal of Food Science, 57*(1), 149-154.

Gutiérrez-Pulido, H., & Salazar, R.D.L.V. (2004). *Análisisy diseo de experimeñtos*. McGraw-Hill.

Kader, A. A. (2013). Postharvest technology of horticultural crops-An overview from farm to fork. *Ethiopian Journal of Applied Science and Technology, 1*(1), 1-8.

León, K., Mery, D., Pedreschi, F., & León, J. (2006). Color measurement in $L^*a^*b^*$ units from RGB digital images. *Food Research International, 39*, 1084-1091.

Lu, F.; Bu, Z. & Lu, S. (2019). Estimating chlorophyll content of leafy green vegetables from adaxial and abaxial reflectance. *Sensor, 19*, 4059**.**

Lunadei, L., Diezma, B., & Lleó, L. (2012). Monitoring of fresh-cut spinach leaves through a multispectral vision system. *Postharvest Biology and Technology, 63*, 74-84.

Martinez, L.M (2021). True colors: Consumers' packaging choices depend on the color of retail environment. *Journal of Retailing and Consumer Services, 59,* 102372**.**

Mendoza, F., & Aguilera, J.M. (2004). Application of image analysis for classification of ripening bananas. *Journal of Food Science, 69*(9), 471-477.

Pedreschi, F., Leo´n, J., Mery, D., & Moyano, P. (2004). Development of a computer vision system to measure the color of potato chips. *Food Research International, 39*, 1092-1098.

Poynton, C. A. (1996). *A technical introduction to digital video*. Wiley.

Saldaña, E. (2013). Review: computer vision applied to the inspection and quality control of fruits and vegetables. *Campinas, 16*(4), 254-172.

U.S. Department of Agriculture. (2020). *Statistics by subject national statistics for lettuce*. https://www.nass.usda.gov /Statistics_bySubject

U.S. Department of Agriculture. (2019). Food availability (per capita) data system. *Vegetable (fresh). 21 May 2020.*. 2019. https://www.ers.usda.gov/data-products/foodavailability-per-capita-data-system.

Zhang, X., & Xu, H. (2009). An adaptively spatial color gamut mapping algorithm. *Chinese Optics Letters, 7*(09), 873-877.

Zhou, T., Harrison, A.D., & McKellar, R. (2004). Determination of acceptability and shelf life of ready-to-use lettuce by digital image analysis. *Food Research International, 37*, 875-881.