Detecting skin defects of star apple by using hyperspectral images

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Abstract. Hyperspectral imaging system with the range of 450–990 nm was used to obtain the reflection spectral of star apples. The hyperspectral image data were used to identify skin defects such as insect bite, fungal infection, rusty spot and scarring of star apples. Principal component analysis (PCA) was used to reduce the spectral dimensionality of hyperspectral image data. Some specific PC images were evaluated visually for showing the difference between the skin defects in two spectral ranges including visible-near infrared and visible ranges. The results of this study can be used as the basis to develop algorithms for the classification of skin defects of star apple.

1. Introduction

Star apple (Chrysophyllum cainito) is a tropical fruit widely planted in Southeast Asia. Depends on the varieties, the skin of ripen star apple may be red-purple, dark-purple, or pale-green. Recently, star apple becomes one of the emerging fruits in Taiwan. Star apple is very vulnerable to skin defects, which affects the quality level as well as the selling price of fresh star apple. Sorting of star apple is an important process during the postharvest process. In Taiwan, currently, there is no sorting standard and automatic sorting facility for star apple. The sorting of star apple is performed mainly based on the basic characteristics of weight, ripe, shape, color, skin defects manually. For red-purple or dark-purple star apples, it is difficult to identify the skin defects by visual inspection or machine vision since the color of red-purple or dark-purple star apples is too dark. Therefore, the quality assurance of star apple is difficult.

Non-destructive methods such as thermal imaging, machine vision, spectroscopy and hyperspectral imaging have been used to investigate the quality of fruit. Thermography has been used to detect codling moth larve in apples [3]. Machine vision has been used for sorting and grading of fruits [4-6]. Furthermore, machine vision systems were used to detect defects of fruit surface with success [7]. However, machine vision is difficult for identifying skin defects of dark skin fruits such as dark-purple star apple. The high signal-to-noise ratio of spectrometer make reflectance spectral useful to assess fruit qualities [9, 10]. Vis-NIR spectroscopy was used to investigate firmness of mango [15]. However, spectroscopy, a point detection method, has difficulty obtaining spatial information of fruit since scanning the surface of fruit point by point takes too much time.

Hyperspectral imaging systems obtain spatial image data with many continuous narrow bands at the same time. The spectrum data at each spatial pixel contains the chemical and physical information of the material were used for non-contact investigation of fruit qualities [16, 17]. Hyperspectral images
expand the ability of using image classification to investigate surface defects of fruit, but at a cost of having to deal with high dimension data sets. Principal component analysis (PCA) is a common methods used to reduce the spectral dimensionality of hyperspectral image data. In this study, hyperspectral imaging system with the range of 450-990 nm was used to investigate the surface defects of dark-purple star apples. Principal component analysis (PCA) was used to reduce the spectral dimensionality of hyperspectral image data of star apples. The PC images of different type of skin defects were analyzed in two spectral ranges including visible-near infrared (vis-NIR) range (450 -990 nm) and visible (vis) range (450-760 nm). The finding of this study could be used to develop algorithms for automatic on-line sorting system of star apples.

2. Material and methods

2.1. Star-apple samples
Dark-purple star apples were obtained from an orchard located in Pingtung, Taiwan. Star apples were stored at room temperature (22°C) and experiments were performed within two days. Fruit samples with normal surfaces and four common defective skin conditions (i.e., insect bite, fungus infection, rusty spot, scarring) were collected. Representative images for each surface condition are shown in Fig. 1. The selected samples and defect types were representative of main and most common defect types on star apple surfaces.

![Insect bite, Fungal infection, Rusty, Scarring](image)

**Figure 1.** Star apple with different surface defect types used in this study.

2.2. Experimental Setup
The hyperspectral imaging system used for this study consists of five main components: Basler ace acA1920-155um monochrome camera, Imaging spectrograph (Inspecor V10, Spectral Imaging Ltd., Oulu, Finland), 50 mm focal length lens, two halogen lamps and a linear stage driven by AC servo motor (HG-KR13, Mitsubishi) with driver (MR-J4-10A1, Mitsubishi). The schematic of this system is shown in Fig. 2a. GUI program developed in Labview environment was used to control the hyperspectral imaging system. All spectral image data were processed by using GUI program developed in Matlab environment (Fig. 2b). A white diffuse board with known reflection efficiency was used to obtain a typical white reference image and the dark current image was obtained by turning off the light sources and covering the lens with opaque cap. The relative reflectance was then calculated from the acquired raw hyperspectral image, white reference and dark reference [18]. The calibrated images with relative reflectance were used for further data analysis. Principal components analysis (PCA) was used to reduce the high dimensionality of hyperspectral image data and the dominant wavelengths were identified from the weighting coefficients of critical PC images.
3. Result and discussion

3.1. Reflection spectra of different star-apple skins

Because the quantum efficiency of CMOS detector is low outside the range of 450–990 nm; therefore, the spectral data within wavelength range of 450–990 nm were used for further analysis. For each type of skin sample, region of interest (ROI) containing about 100 pixels were selected manually and the representative reflectance spectra were obtained by averaging spectral information of all pixels in ROI. The representative reflectance spectra of star apple samples with normal surfaces and four common defective surface conditions (i.e., insect bite, fungal infection, rusty spot, scarring) in a wavelength range of 450–990 nm, are presented in Fig. 3.

It can be seen from Fig. 3 that spectral shape of normal and insect bite skin defect are relatively similar among the spectra from 450 nm to 750 nm but the reflectance values of normal skin above 780 nm are lower than those of insect bite skin. Furthermore, fungal infection and rusty spot have similar spectral characteristics except the reflectance values of fungal infection skin between 560-740 nm are lower than those of rusty spot skin. It is worth to mention that the scarring surface has the highest reflectance values among the wavelength range of interest (450-990 nm). The possible reason is that the light is reflected from lignification flesh cells instead of skin since the skin of scarring surface has been removed.

![Figure 3. Averaged reflection spectra of different surface types of star apple.](image-url)
3.2. Principal component analysis
PCA was applied to the hyperspectral image data of the star apples with vis-NIR and vis spectral ranges (450-990 and 450-760 nm). In order to avoid interference from the background about the PCA analysis, portion of image containing only the fruit was used for PCA analysis by applying binary mask to the image data. Then, each PC image was visually investigated to determine which PC image can show the major difference between defect and normal portion on the sample surface.

3.2.1. PCA by using VIS-NIR spectra (450-990 nm). The first three PC images obtained from the PCA of the hyperspectral reflectance images of different types of samples using all the spectral bands (450-990 nm) are shown in Fig. 4a. In order to obtain a clearer comparison, RGB images of sample are shown in the first row of Fig. 4a. It can be seen from Fig. 4a that the first three PC images show that major defect features became more obvious in some PC images. Finding a specific PC image (PC1-PC3) to detect all types of skin defects is difficult. However, there is an obvious contrast between normal skin and four types skin defects in some specific PC images. Therefore, these PC images, including PC2 for insect bite, fungal infection and rusty spot surfaces; PC3 for scarring surface can be used to extract those specific defects. The weighting coefficients for the specific PC images obtained using images across the entire spectral region are shown in Fig. 4b. Local maximum or minimum in the curves represents significant bands. By comprehensively analyzing the weight coefficients of specific PC images of different types of samples, it could be found in Fig. 4b that wavelengths centered at 538, 639, 736 and 950 nm can be selected as characteristic wavelengths for further analysis.

![PC images of different type of skins by using vis-NIR spectra for (a) insect bite, (b) fungus infection, (c) rusty spot, (d) scarring, respectively and weighting coefficients for the specific PC components which can best identify the skin defects.](image)

3.2.2. PCA by using vis spectra (450-760 nm). The resultant PC images using visible spectral bands (450-760 nm) are shown in Fig. 5a. In order to obtain a clearer comparison, RGB images of samples are also shown in the first row of Fig. 5a. It can be seen from Fig. 5a that features of insect bite, rusty spot, scarring skin can be clearly identified in PC3, PC2 and PC2 respectively. However, the defect features of fungal infection skin cannot be identified in the first three PC images. The weighting coefficients for the specific PC images obtained using images using the data within visible range are shown in Fig. 5b. Local maximum or minimum in the curves represents significant bands. By investigating the weight coefficients of specific PC images of different types of specimens, it could be found from Fig. 6b that wavelengths centered at 685 and 714 nm could be selected as the characteristic wavelengths for further analysis.
Figure 5. PC images of different type of skins by using vis spectra for (a) insect bite, (b) fungus infection, (c) rusty spot, (d) scarring, respectively and weighting coefficients for the specific PC components which can best identify the skin defects.

4. Conclusions
In this study, push broom hyperspectral imaging system with a usable spectral range of 450-990 nm was used to obtain the hyperspectral image data of star apples. The feasibility of using hyperspectral imaging and PCA for detecting common skin defects of star apples was investigated. This study showed that hyperspectral imaging technique has the potential to be used for surface defect detection of dark-skin star apples. The optimal wavelengths selected from the local maximum and minimum of specific PC’s weight coefficient can be used to develop algorithms for identification and classification of star apple defects in a real-world sorting situation. Future work will focus on (1) integrating PCA on selecting optimal wavelengths for band ratio methods for simplified algorithms of surface defect detection of star apples, and (2) developing a more efficient rotational hyperspectral scanning system for the on-line detection of star-apple surface defects.

References
[1] Xie, A.G., D.W. Sun, Z.W. Zhu and H.B. Pu, 2016 Food Bioprocess Technol. 9 1444
[2] Kamruzzaman, M., Y. Makino and S. Oshita, 2016 Meat Sci. 116 110
[3] Kamruzzaman, M., Y. Makino and S. Oshita, 2016 LWT Food Sci. Technol. 66 685
[4] Cheng, W.W., D.W. Sun, H.B. Pu and Q.Y. Wei, 2017 Food Chem. 221 1989
[5] Ye, X.J., K. Lino and S.H. Zhang, 2016 Meat Sci. 122 25
[6] Cheng, W.W., D.W. Sun, H.B. Pu and Y.W. Liu, 2016 LWT Food Sci. Technol. 72 322
[7] Tao, F.F., Y.K. Peng and Y.Y. Li, 2015 Int. J. Agric. Biol. Eng. 8 95
[8] Li, H.H., Q.S. Chen, J.W. Zhao and M.Z. Wu, 2015 LWT Food Sci. Technol. 63 268
[9] Kim, J., A. Mowat, P. Poole and N. Kasabov, 2000 Chemom. Intell. Lab. Syst. 51 201
[10] Park, B., J.A. Abbott, K.J. Lee, C.H. Choi and K.H. Choi, 2003 Trans ASAE 46 1721
[11] Xing, J., C. Bravo, D. Moshou, H. Ramon and J. De Baerdemaeker, 2006 Comput. Electron. Agric. 52 11
[12] Xing, J., V. Van Linden, M. Vanzeebroeck and J. De Baerdemaeker, 2005 Food Control 16 357
[13] Travers, S., M.G. Bertelsen, K.K. Petersen and S.V. Kucheryavskiy, 2014 LWT Food Sci. Technol. 59 1107
[14] Li, J.B., W.Q. Huang, C.J. Zhao and B.H. Zhang, 2013 J. Food Eng. 116 324
[15] Kamruzzaman, M., Y. Makino and S. Oshita, 2016 Food Chem. 196 1084
[16] Liu, G.S., J.G. He, S.L. Wang, Y. Luo, W. Wang, L.G. Wu, Z.H. Si and X.G. He, 2016 Int. J. Food Prop. 19 41
[17] Li, J.B., L.P. Chen, W.Q. Huang, Q.Y. Wang, B.H. Zhang, X. Tian, S.X. Fan and B. Li, 2016
[18] ElMasry, G., N. Wang and C. Vigneault, 2009 *Postharvest Biol. Technol.* **52** 1
[19] Xiong, Z.J., D.W. Sun, Q. Dai, Z. Han, X.A. Zeng and L. Wang, 2015 *Food Anal. Methods* **8** 380