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# Detection of Hidden Bruise on Kiwi fruit Using Hyperspectral Imaging and Parallelepiped Classification

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**Abstract**

It is necessary to develop non-destructive detection techniques of kiwi fruit because machine injury could lower the quality of fruit and incur economic losses. Owing to the special physical properties of kiwi fruit peel, the bruises are not visible externally. Its could not be effectively inspected using conventional non-destructive detection technology. We proposed the hyperspectral imaging technique to inspect the hidden bruises on kiwi fruit in this work. The Vis/NIR (408-1117 nm) hyperspectral image data was collected. The top four component images were obtained from the data which ranged from 600 to 1000 nm using principal component analysis, and the bruise regions were extracted from the component images using parallelepiped classification. The experimental results show that the error of detecting hidden bruises on fruits with hyperspectral imaging was 14.5 %.



Keywords: Detection. Hyperspectral imaging. Hidden bruise. Kiwi fruit. Parallelepiped classification. Principal component analysis(PCA)

## 1.Introduction

Kiwi fruit, which is nutritious and sweet in flavor, is one of the most favourite fruits for population. As the origin of kiwi fruit, the planting area and production in china rank first in the world. However, excessive mechanical loading and stress cause injuries to kiwi fruits during the processes of harvesting, transport, handling, and storage. The bruises lower the quality of the fruits and cause significant economic losses because such fruits easily ferment, rot, or get mildewed, and infect other normal fruits during the storage.


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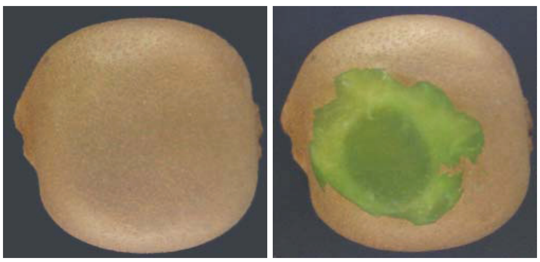
So, it is necessary to develop a detection technique for distinguishing the bruised kiwi fruits from the normal fruits.

In the past two decades, a number of techniques for an automated non-destructive detection of fruits and vegetable quality have been reported, such as machine vision for shape classification and defect detection[1-3], X-ray imaging for inspection internal quality[4,5], and near infrared (NIR) spectroscopy for prediction internal indicators[6,7]. However, to our knowledge, no research has been conducted for the non-destructive detection of hidden mechanical bruises on kiwi fruits. Because of the toughness and taupe of kiwi fruit peel, the bruises can't be expressed on the peel. It is difficult to be detected by human inspectors or visible imaging. The fruit juice quickly gathers in the bruises regions after the fruit tissue has been damaged. Because the water content of kiwi fruit is high, the qualitative difference between the bruises regions and normal regions is not sufficient to distinguish the defective fruits using X-ray imaging. As a point source detection technique, NIR spectroscopy can't be used to collect spatial information of fruits quality.

The hyperspectral imaging combines conventional spectroscopy and imaging techniques to acquire both spectral and spatial information from an object. It can meet the demands of non-destructive detection for fruits bruises. In the recent years, hyperspectral imaging has been investigated for bruises and bitter pit in apple[7-12]. Cai et al. studied hyperspectral imaging for detecting rust in citrus[13]. The overall objective of this research was to investigate the potential of using hyperspectral imaging in visible and near-infrared (Vis/NIR) region for detection of bruises on kiwi fruit. The hyperspectral image data was collected. The top four images were obtained from the data using principal component analysis, and the bruise regions were extracted from the component images using parallelepiped classification.

## 2.Materials and Methods

**Sample Preparation.** The kiwi fruit tested in this study was 'Zhonghua' kiwi fruit, which produced in Zhouzhi County, Shaanxi Province, China. Two hundred non-bruise kiwi fruits were manually selected through visual and touch inspection, and purchased from a local Zhenjiang supermarket in October, 2008. The kiwi fruits were randomly divided into two groups of 100 samples in each of them. The first group was used as control (normal kiwi fruits); another one contained bruise kiwi fruits damaged artificially. Samples of both two groups were stored at room temperature (25 ± 1 ℃) for 24 h before being measured. There were no obvious bruise features on the kiwi fruits surface detected by visual inspection. When hyperspectral image data were collected, all fruits were peeled to detect the presence of bruises. Color images of bruised kiwi fruit before and after peeling are shown in Fig. 1.



(a) (b)

Fig. 1. Color images of bruises kiwi fruit obtained before (a) and after (b) peeling of skin

**Hyperspectral Imaging System.** The scheme of the hyperspectral imaging system, developed for this study, is shown in Fig. 2. The system is composed of three major units. The imaging unit has a complementary metal oxide semiconductor (CMOS) camera (BCi4-U-M-20-LP, Vector International, Leuven, Belgium), and an imaging spectrograph (ImSpector V10E, Specim Spectral Image Ltd., Oulu, Finland) coupled with a 23 mm focal length C-Mount zoom lens. The ImSpector spectrograph has a fixed-size internal slit to define the field of view for the spatial line and a prism-grating-prism (PGP) system for the separation of the spectra along the spatial line. The lighting unit is a DC regulated light source from a 150W tungsten halogen lamp (DC-950A, Dolan-Jenner Industries Inc., Massachusetts, USA) delivered through dual fiber optic light lines (QDF3948, Dolan-Jenner Industries Inc., Massachusetts, USA). The conveyer unit consists of a motorized translation stage (TSA200-A, Zolix Instruments Co., Beijing, China), and a motion controller (SC300-1A, Zolix Instruments Co., Beijing, China). The spectral range of the hyperspectral camera is from 408 nm to 1117 nm with 0.69 nm spectral intervals, which resulted in 1024 spectral bands.

**Software.** For hyperspectral image acquisition, SpectralCube (AutoVision Inc., California, USA) was used. All data processing and analysis procedures described above were performed using Environment for Visualizing Images (ENVI) V.4.5 (Research Systems Inc., Colorado, USA) and MVTec Halcon 8.0 (MVTec Software GmbH, München, Germany) for windows XP.

**Hyperspectral Image Data Acquisition.**The hyperspectral imaging system is a push broom and line-scan based imaging system. The kiwi fruit was put on the translation stage in this system to begin data acquisition. The CMOS camera is a linear array detector with a 1280 by 1 pixel resolution in a scanned line. The camera and spectrograph were used to scan the fruit line-by-line as the translation stage moved the fruit through the field of view of the optical system. After finishing the scans on one entire kiwi fruit, the spatial-by-spectral matrices were combined to construct a three-dimensional (3D, 1280 × 500 × 1024) spatial and spectral data space.

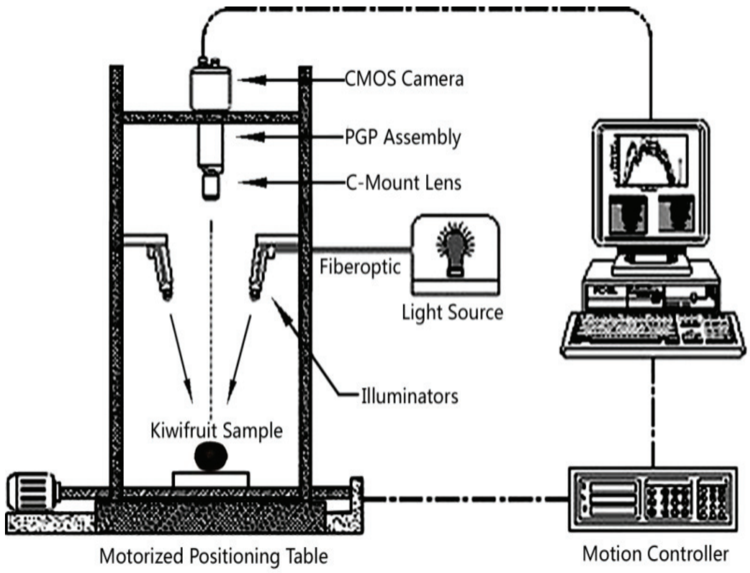



Fig 2. Sketch of hyperspectral imaging system

**Image Calibration.** The hyperspectral images of the kiwi fruits were first calibrated with a white and a dark reference using the following equation:

$$R = \frac{I - B}{W - B} \tag{1}$$

Where $R$ is the relative corrected reflectance image, $I$ is the original hyperspectral image of kiwi fruit, $B$ is the dark image (approximately 0% reflectance) recorded by turning off all light sources and covering the lens with a black cap, and $W$ is the white image obtained by a reference panel (Spectralon, Labsphere Inc., New Hampshire, USA) with approximately 99% reflectance. The representative calibrated reflectance spectra (408 – 1117 nm), which were obtained from this hyperspectral imaging system, are demonstrated in Fig. 3.

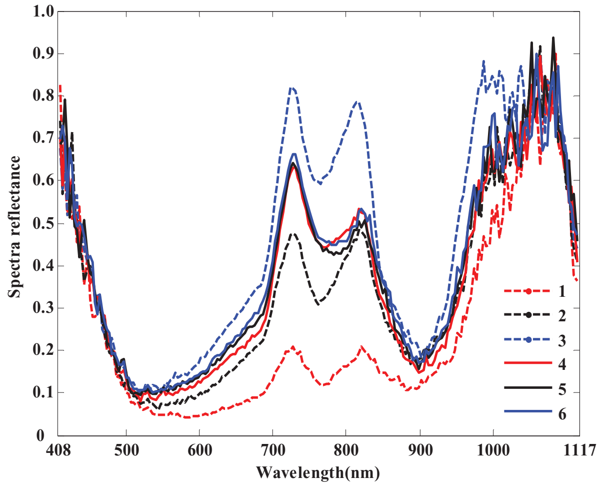



Fig. 3. Spctral profiles (408 nm-1117 nm) of bruises kiwi fruit

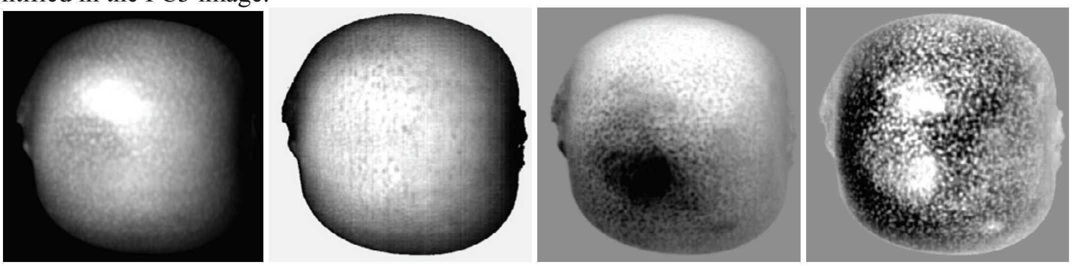
## 3.Results and Discussion

**Data Preprocessing.** Fig. 3 shows the average spectral profiles of different regions (50×50 pixels, three normal regions (No.1-3), and three bruise regions (No.4-6)) of a single sample. According to Fig. 3, the spectral profiles of kiwi fruit were very close in the spectral regions below 600 nm, and there is a high noise level over 1000 nm. Therefore, the spectral region of 600-1000 nm was used in the next analysis, and thus there were 580 spectral bands in the spectral region.

In order to remove noise and redundant data, the average of every five pixels after calibration in the spectral dimension was used in the succeed analysis. 520 pixels from 281 to 800 were selected in the horizontal (X-axis) direction to ensure kiwi fruit image integrated, thus the 3D data cube was 520 × 500 × 116, which greatly decreased dataset. Before doing further data processing, the background of the image was removed by the simple thresholding method. A mask was built from the image at 650 nm when the threshold was set 0.09. The mask was applied to get the area of kiwi fruit from the hyperspectal image data. The resultant images were further processed by principal component analysis (PCA) and parallelepiped classification.

**Principal Component Analysis(PCA).** PCA is a very effective data reduction technique for spectroscopic data[14,15]. It summarizes data by forming new variables, which are linear composites of the original variables. In this study, PCA was performed to reduce spectral dimensionality and enhance image features. There was large amount of hyperspectral images, so PCA was used to find several dominant spectral band images (i.e. optimal band images) in order to minimize the amount of data without sacrificing detection results.

The hyperspectral data were preprocessed as described above: reflectance calibration, data reduction, and background removal. Afterwards, PCA was performed on the hyperspectral data (600-1000 nm) of each kiwi fruit, and hence the large amount of hyperspectral data of each fruit was represented by several principal component images. The top four principal component images (PC1 to PC4) are shown in Fig. 4. According to visual inspection, the PC1 mainly represents the grey value of the kiwi fruit, while the PC3 demonstrates more sufficient information about the fruit quality. The bruise region could be clearly identified in the PC3 image.



(a)PC1 (b)PC2 (c) PC3 (d)PC4

Fig. 4. Top 4 principal component images

**Parallelepiped Classification.** Parallelepiped classification is a widely used decision rule based on simple Boolean logic[14,15]. Training data in n spectral bands are used in performing the classification. Brightness values from each pixel of the multi-spectral imagery are used to produce an n-dimensional mean vector, $M_c$. Where $M_c = (\mu_{c1}, \mu_{c2}, \mu_{c3}, \ldots, \mu_{cm})$ with $\mu_{ck}$, being the mean value of the training data obtained for class $c$ in band $k$ out of $m$ possible classes. $S_{ck}$ is the standard deviation of the training class $c$ in band $k$ out of $m$ possible classed. Using one standard deviation threshold, a parallelepiped algorithm decides $BV_{ijk}$ is in class $c$, if

$$\mu_{ck} - S_{ck} \leq BV_{ijk} \leq \mu_{ck} + S_{ck} \tag{2}$$

Where $c = 1, 2, 3, \cdots, m$ number of classes, $k = 1, 2, 3, \cdots, n$ number of bands; thus the low and high decision boundaries are defined as

$$Low_{ck} = \mu_{ck} - S_{ck} \tag{3}$$

and

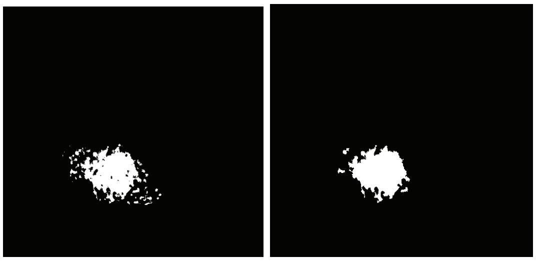
$$High_{ck} = \mu_{ck} + S_{ck} \tag{4}$$

The parallelepiped algorithm becomes

$$Low_{ck} \leq BV_{ijk} \leq High_{ck} \tag{5}$$

These decision boundaries form an n-dimensional parallelepiped in future space. If the pixel value lies above the lower threshold and below the high threshold for all n bands evaluated it is assigned to that class . If the pixel value does not meet any of the rules, it is assigned to the unknown class.

In order to segement the bruise regions from the top four component images of kiwi fruit using parallelepiped classification, regions of interest (ROIs) in bruise area were generated as training data for bruises, and its mean values and standard devations in all four component images were obtained. After several trails, the performence of the algorithm was best when the standard devation threshold was set at 4. The binary image of bruise region obtained using parallelepiped classification was shown in Fig. 5a. There were some small noise regions in Fig.5a. Bruise regions obtained using morphology processing such as hole filling and size filtering are shown in Fig.5b.



(a) (b)

Fig. 5 Results after (a) parallelepiped classifying and (b) morphology processing

**Bruise Detection.** The proposed system (included the hardware and the algorithm) has been used to test 'zhonghua' kiwi fruits. The results obtained by the system are given in Table 1. The total error rate reached 14.5%, the positive error (normal fruits were classified as bruise fruits) was 16.2%, and the false error (bruise fruits were classified as normal fruits) was 12.6%. The transmission and reflection of peel were inconsistent because of the existence of the spot and rust on the surface of kiwi fruit. So the rust and spot area was segmented as bruise, which was the main reason of positive error, and the main reason of false error was the artificial injury on kiwifruit that was too light to segment.

Table 1. Results of hidden bruises detection on kiwi fruits

| Sample | Number | Detection results | |
|---|---|---|---|
| | | Normal(95) | Bruises(105) |
| Normal | 100 | 83 | 17 |
| Bruise | 100 | 12 | 88 |
| Classification error (%) | | 12.6 | 16.2 |
| Total | 200 | 14.5 | |

## 4.Conclusion

A Vis/NIR hyperspectral imaging system was developed to detect hidden bruises on kiwi fruits in wavelength range from 408 nm and 1117 nm. This system can acquire both spatial and spectral information from an object simultaneously. An image processing algorithm using PCA and parallelepiped classification for the component images of multiple waveband images was developed for determining whether kiwi fruit was normal or bruises. The total detection error rate was 14.5%. This study laid a foundation for further development of an in-line inspection system using hyperspectral imaging technique for bruise detection on kiwi fruits.

## Acknowledgements

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## References

[1] J.A. Throop, D.J. Aneshansley, W.C. Anger, et al. Quality evaluation of apples based on surface defects: development of an automated inspection system. *Postharvest Biology and Technology*, 2005, 36(3): 281-290.

[2] B. Zhu, L. Jiang, Y.G. Luo, et al. Gabor feature-based apple quality inspection using kernel principal component analysis. Journal of Food Engineering, 2007, 81(4):741-749.

[3] X.B. Zou, J.W. Zhao, Y.X. Li, et al. In-line detection of apple defects using three color cameras system. *Computers and Electronics in Agriculture*, 2010, 70(1): 129-134.

[4] S. Kim, and T.F. Schatzki. Apple watercore sorting system using x-ray imagery: I. Algorithm development. *Transactions of the ASAE*, 2000, 43(6): 1695-1702.

[5] N. Kotwaliwale, P.R. Weckler, G.H. Brusewitz, et al. Non-destructive quality determination of pecans using soft X-rays. *Postharvest Biology and Technology*, 2007, 45(3): 372-380.

[6] J. Lammertyn, B. Nicolaï, K. Ooms, et al. Non-destructive measurement of acidity, soluble solids, and firmness of Jonagold apples using NIR-spectroscopy. *Transactions of the ASAE*, 1998, 41(4): 1089-1094.

[7] Xingyue Hu, Yong He, Annia García Pereira, et al. Nondestructive Determination Method of Fruit Quantity Detection Based on Vis/NIR Spectroscopy Technique. *Engineering in Medicine and Biology 27th Annual Conference*. Shanghai. China. September, 2005.

[8] J. Xing, and J.D. Baerdemaeker. Bruise detection on 'Jonagold' apples using hyperspectral imaging. *Postharvest Biology and Technology*, 2005, 37(2): 152-162.

[9] H.K. Noh, and R. Lu. Hyperspectral laser-induced fluorescence imaging for assessing apple fruit quality. *Postharvest Biology and Technology*, 2007, 43(2): 193-201.

[10] P.M. Mehl, Y.R. Chen, M.S. Kim, et al. Development of hyperspectral imaging technique for the detection of apple surface defects and contaminations. *Journal of Food Engineering*, 2004, 61(1): 67-81.

[11] B.M. Nicolaï, E. Lötze, A. Peirs, et al. Non-destructive measurement of bitter pit in apple fruit using NIR hyperspectral imaging. *Postharvest Biology and Technology*, 2006, 40(1): 1-6.

[12] J.W. Zhao, J.H. Liu, Q.S. Chen, et al. Detecting Subtle Bruises on Fruits with Hyperspectral Imaging. *Transactions of Chinese Society of Agricultural Machinery*, 2008, 39(1):106-109. (in Chinese)

[13] J.R. Cai, J.H. Wang, Q.S. Chen, et al. Detection of rust in citrus by hyperspectral imaging technology and band ratio algorithm. *Transactions of Chinese Society for Agricultural Engineering*, 2009, 25(1): 127-131. (in Chinese)

[14] J.A. Richards. *Remote Sensing Digital Image Analysis: An Introduction*. Berlin: Springer-Verlag, 1999.

[15] J.R. Jensen. *Introductory Digital Image Processing: A Remote Sensing Perspective*. Upper Saddle River, N.J.: Pearson /Prentice Hall, 2005.