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From hyperspectral imaging to multispectral imaging: Portability and stability of HIS-MIS algorithms for common defect detection

Baohua Zhang, Longshen Liu, Baoxing Gu, Jun Zhou*, Jichao Huang, Guangzhao Tian

College of Engineering, Nanjing Agricultural University, Nanjing 210031, Jiangsu, PR China

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ABSTRACT

The portability and stability of algorithms from hyperspectral imaging (HIS) to multispectral imaging (MIS) for detection of common defects on fruits is limiting the commercialization of multispectral inspection systems. The efficiency of selected wavelengths, the robustness to physical and biological variability, and the transplantation of the classification algorithms affect the portability and stability of algorithms from HIS to MIS. Apples with wind damage, insect damage, bruises, decay, hail, russeting, spot, scar, stem, calyx, as well as with sound surfaces were studied. Different image recognition methods were proposed according to the defect type and spectral characters. For common defects, the overall detection accuracy of 93.6% for HIS data and 91.4% for MIS with the same wavelengths and same methods was obtained. The uneven lightness distribution in the spectral images was also investigated and eliminated by the band math or partial least squares (PLS) model based methods Principal component analysis, minimum noise fraction, band math, particle least square model based methods were also investigated and compared. Results show that band math and model based method possess a higher portability and stability from HIS to MIS, and the proposed methods could make the variation of illumination, physical and biological variability as negligible interference in common defect detection. This study could provide potential reference for promoting the development of MIS and the applications of transplantable algorithms in HIS.

1. Introduction

Surface defects in fruit and vegetables are important external sensory quality attributes that influence their market value and consumer purchasing behavior (Zhang et al., 2014; Li et al., 2013). Grading agricultural products according to their external and internal quality increases their economic value and satisfies customers (Pu et al., 2015; Wu and Sun, 2013).

In recent years, HIS techniques have been developed as an efficient tool for non-destructive inspection of food and agricultural product quality (Nicolaï et al., 2006; Gowen et al., 2007; ElMasry et al., 2012; Fan et al., 2016). Computer vision technique imitates the human vision by capturing three monochromatic images at red, green, and blue wavelengths. However, it is less useful when applied in the detection of defects which are not sensitive to visible light. HIS techniques integrate both the imaging and spectroscopic techniques into one system. It can acquire a set of monochromatic images at almost continuous hundreds of thousands of wavelengths. HIS systems could provide both spatial information, the same as conventional imaging systems, for each wavelength of the full spectrum, and spectral information, the same as spectroscopic device, for each pixel of the spatial images. The data structure of hyperspectral image is commonly called ‘hypercube’, or data cube. A hyperspectral image could be considered as a stack of two-dimensional images at almost continuous wavelengths, or a set or full spectra of each pixel in one two-dimensional image cluster together (Liu et al., 2015). The most advantage of a hyperspectral image is the extensive information contained with the image. Defects might be very clear in one single monochromatic image or become easy to recognize in several monochromatic images or combining images. As a result, hyperspectral imaging has been widely used in fruit surface defect detection (Zhang et al., 2015a,b,c; Li et al., 2016; Yu et al., 2014a,b; Lorente et al., 2013; Lee et al., 2014; Wu et al., 2016; Jiang et al., 2016; Cho et al., 2013; Lu et al., 2016; Baranowski et al., 2013).

However, the extensive information of hyperspectral image data also brings some drawbacks, such as long time required to acquire the image, as well as the complexity of image processing and analyzing (Liu et al., 2015; Zhang et al., 2015a,b,c; Dai et al., 2015). These drawbacks limit it’s commercialization in fast grading lines. Actually, hyperspectral imaging is always used to acquiring images with high spatial and spectral resolutions for off-line application and optimal wavelength

* Corresponding author.
E-mail address: zhoujun@njau.edu.cn (J. Zhou).

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selection. To realize the fast in-line inspection required by the industry, the transformation from fundamental research to fast application is needed. Multispectral imaging aims to acquire spatial and spectral information that is directly useful for real-time applications (Qin et al., 2013). Multispectral imaging can keep the advantage of rapidity as computer vision systems, as well as the advantage of containing efficient wavelengths as hyperspectral imaging. Because of these advantages, MIS has become the goal of replacing HIS for rapid and non-destructive inspection of the quality of food and agricultural products in most applications. Several prototypes of multispectral imaging systems (MIS) have been developed for detection of citrus canker and defects (Qin et al., 2012; Blasco et al., 2007; Aleixos et al., 2002; Kumar and Lee, 2012), detection of defects on apples (Kleynen et al., 2005; Huang et al., 2015). Meanwhile, commercial multispectral cameras also support the use of customized user-selected filters for specific application.

The ultimate goal of hyperspectral imaging should seek its task in serving fast grading lines for rapid and non-destructive inspection of fruit quality. Papers have focused on the inspection methods (including image processing and spectral analyzing) by using HIS, and verification performance using similar processing methods based on the images at selected wavelengths extracted from hyperspectral images. Less attention has been paid to portability and stability of algorithms from HIS to MIS for detection of common defects on fruits.

Principal component analysis (PCA) and minimum noise fraction (MNF) are the two efficient and commonly used HIS processing methods for fruit defect detection (Xing and De Baerdemaeker, 2005; Xing et al., 2007a,b). PCA and MNF are unsupervised classification methods; they develop classification labels automatically without having foreknowledge of the classes and identify similarity between key features of image and spectral data by using clustering algorithms (Liu et al., 2014). Therefore, the accuracy of unsupervised classification methods is highly depended on the experimental conditions, such as arrangement and type of light source, lightness distribution. The factors that influence the portability and stability of algorithms from HIS to MIS include: (1) Whether the selected wavelengths that are optimal and suitable for MIS systems are the same as for HIS systems; (2) Whether the algorithms are robust to variations in illumination condition, as well as physical and biological variability of inspected samples; (3) The transplantation and efficiency of the algorithms from HIS to MIS. Besides, the uneven distribution of lightness of the curved surface and similarity between calyx/stem and true defects are also two adverse factors that influence detection performance (Li et al., 2013; Zhang et al., 2015a,b,c, 2014; Xiao-bo et al., 2010; Zhang et al., 2017).

The main objectives of this paper were to investigate the portability and stability HIS-MIS algorithms for detection of common defects in apples, and develop robust and efficient image and spectral inspection algorithms for common defect detection which could make the variation of illumination, as well as physical and biological variability as negligible interference for common defect detection from HIS to MIS.

2. Materials and methods

2.1. Apple samples and common defects

'Fuji' apple were hand-picked from the commercial orchard in Changping district, Beijing during the harvest season or brought from a local fruit supermarket in Haidian district, Beijing, 2015. The diameters of the samples vary from 65 mm to 90 mm. Fruits with normal surface and several types of common defects (wind damage, insect damage, russeting, hail, spot, scar, bruise and decay) were collected. The defects were divided into different types according to spectral and spatial characters. Representative images of the defects, calyx/stem, and sound tissues are shown in Fig. 1.

2.2. Hyperspectral image acquisition system

Fig. 2 shows the configuration of the HIS used in our research. The hardware and corresponding parameters could be found in our previous literature Zhang et al. (2015a,b,c). The detailed information of the HIS is as following: exposure time: 26 ms, frame rate: 12.4, image size: 1004 × 1000, fruit speed: 0.8 mm/s, method of orientation: random, effective wavelength range: 400–1000 nm.

The software in our research was provided by Isuzu Optics Corp, Taiwan, China. The HIS acquisition parameters, speed of the motor, and start and end positions of the acquisition could be set by the software.

The HIS image acquired is the signal intensity of the uncorrected radiance from the fruit. To obtain the reflectance image, the hyperspectral reflectance image R for a spatial pixel (i) at a given wavelength was calculated by using the following equation (Lee et al., 2014):

$$R_i = \left(\frac{RS_i - RD_i}{RW_i - RD_i}\right) \times 100\% \tag{1}$$

where RS, RD, and RW are the intensity values of identical pixels from the sample image, dark reference image, and white reference image, respectively. R_i is the corrected hyperspectral reflectance image. The dark reference image RD (with ~0% reflectance) represents the dark response of the camera, and can be acquired by measuring a spectral image with the light source turned off completely and the camera lens covered completely with its non-reflective opaque black cap. The white reference image RW (with ~99.9% reflectance) represents the highest reference intensity values, and can be acquired by measuring a spectral image of the Teflon white board with a 99.9% reflectance. All the multivariate analysis, band math methods and image processing would be conducted on the hyperspectral reflectance images in this research.

2.3. Multispectral imaging system and hand-coded software

Fig. 3 shows the configuration of the developed multispectral imaging system and hand-coded software used in our research. The hardware of the MIS system generally consists of the following components: A computer (Dell, Inter(R) Core(TM) i5-2400 CPU @3.10 GHz, Random Access Memory (RAM) 4.0GB), a Charge-Coupled Device (CCD) camera (JAI AD-080GE2CCD Multi-spectral camera, Japan) with high spatial resolution (1024 × 768 pixels, Red, Green, Blue (RGB) image), and a high sensitivity in the near infrared area (800 nm, Near Infrared Red (NIR) image), two 150-W halogen lamp assemblies (3900-ER, Illumination Technologies, Inc., USA), an optical 6 position filter wheel with (FW102C, Thorlabs, Rogers, Minnesota, United States), five filters with the center at 610 nm, 730 nm, 820 nm, 850 nm, and 930 nm. The hand-coded software was developed by using VC++, MFC and Open Source Computer Vision (OpenCV). The developed MIS is just for the research of the portability and stability of HIS-MIS algorithms for common defect detection, a more commercial MIS developed by our previous team led by Pro. Chunjiang Zhao and Dr. Wenqian Huang in National Engineering Research Center for Information Technology in Agriculture (NERCITA) can be found in the literature (Huang et al., 2015).

2.4. Image and spectral processing and analysis methods

PCA is the most widely used approach in the hyperspectral image data analysis for the external quality inspection of food and agricultural products (Liu et al., 2014; Feng and Sun, 2012; ElMasry et al., 2012; Xing et al., 2007b; Zhang et al., 2015a; Li et al., 2013). PCA transforms the hyperspectral image into sequence of principal component images where the first several component images can be used to represent the majority of the information contained in the original HIS. Minimum noise fraction (MNF) rotation is also commonly used in the HIS analysis. MNF is a more complex transformation containing two cascaded PCA transformations of the raw hyperspectral image. More detailed