Food Control 66 (2016) 215–226

Contents lists available at ScienceDirect

Food Control

journal homepage: www.elsevier.com/locate/foodcont

Real-time pixel based early apple bruise detection using short wave infrared hyperspectral imaging in combination with calibration and glare correction techniques

Janos C. Keresztes*, Mohammad Goodarzi, Wouter Saeys

KU Leuven, Department of Biosystems, MeBioS, Kasteelpark Arenberg 30, 3001 Leuven, Belgium

A R T I C L E I N F O

Article history:
Received 9 December 2015
Received in revised form
4 February 2016
Accepted 5 February 2016
Available online 12 February 2016

Keywords:
Hyperspectral imaging
Food sorting
SWIR
Real-time
Glare correction
Uniform illumination
Pixel-based classification
Short wave infrared

A B S T R A C T

High speed data processing for online food quality inspection using hyperspectral imaging (HSI) is challenging as over hundred spectral images have to be analyzed simultaneously. In this study, a real-time pixel based early apple bruise detection system based on HSI in the shortwave infrared (SWIR) range has been developed. This systems consists of a novel, homogeneous SWIR illumination unit and a line scan camera. The system performance was tested on Jonagold apples bruised less than two hours before scanning. Partial least squares-discriminant analysis was used to discriminate bruised pixel spectra from sound pixel spectra. As the glossiness of many fruit and vegetables limits the accuracy in the detection of defects, several reflectance calibrations and pre-processing techniques were compared for glare correction and maximizing the signal to noise ratio. With the best combination of first derivative and mean centering, followed by image post-processing, this system was able to detect fresh bruises in thirty apples with 98% accuracy at the pixel level with a processing time per apple below 200 ms.

1. Introduction

Over 80 million tons of apples are produced worldwide every year, with a production growth of 3.10% and a yield growth of 2.31% (FAOSTAT, 2016). Bruising is one of the most important causes of commercial loss in the apple industry. Bruises usually occur by impact damage during harvest, transportation, cleaning or on the sorting line (Van Zeebroeck et al., 2007). In the bruised regions, the damaged cells release their content in the apple matrix such that polyphenol is exposed to oxygen, resulting in browning of the tissue. This is not appreciated by consumers (Soliva-Fortuny, Grigelmo-Miguel, Odriozola-Serrano, Gorinstein, & Mart'in-Belloso, 2001). Traditionally, bruised apples are identified through visual inspection and removed manually, which is a laborious task. Therefore, there is a demand for machine vision technology for rapid and non-destructive, early bruise detection in apples.

Machine vision technology is already widely used in the apple industry for on-line sorting automation (Blasco, Aleixos, & Moltó, 2003; Cubero, Aleixos, Moltó, Gómez-Sanchis, & Blasco, 2011). However, this technology fails to effectively detect bruises in several apple varieties with detection accuracies as low as 63% (Soliva-Fortuny et al., 2001). Moreover, small or fresh bruises often remain undetected as the spectral signatures of healthy and bruised regions in the visible range (400–700 nm) are very similar shortly after bruising when the oxidative browning is still limited (Kleynen, Leemans, & Destain, 2005). Furthermore, the stalk or calyx of apples should not face the imager (Wenqian Huang, Chi Zhang, Jiangbo Li, Liping Chen, & Chunjiang Zhao, 2012), because these

Acronyms: BG, Background; CV, coefficient of variability; DN, digital numbers; FAOSTAT, food and agriculture organization statistical database; FF, false negatives; FP, false positives; FPA, Focal plane array; HgCdTe, mercury cadmium telluride; HPLC, high performance liquid chromatography; im. Proc, image processing; InGaAs, Indium Gallium Arsenide; iPLS, interval partial least squares; iPLS-DA, interval partial least squares discriminant analysis; LV, latent variable; MCT, Mercury Cadmium Tellurium; MC, mean centering; MSC, multiplicative scatter correction; N, number of negatives; PBR, pixel based reflectance; PBARC, pixel based with absolute reflectance correction; PCA, principal component analysis; PXI, rugged PC-based platform for measurement and automation systems; RGB, red green blue; ROI, region of interest; RMSEC, root mean squared error of calibration; RMSECV, root mean squared error of cross validation; RMSEP, root mean squared error of prediction; RPM, reference pixel method; SNR, signal to noise ratio; SNV, standard normal variate; T, number of positives; TN, true negatives; TP, true positives; VLAM, Vlaams Centrum voor Agro-en Visserijmarketing.

* Corresponding author.
E-mail address: janos.keresztes@biw.kuleuven.be (J.C. Keresztes).

http://dx.doi.org/10.1016/j.foodcont.2016.02.007
0956-7135/

are often interpreted as bruises by the computer vision systems (Wen & Tao, 1999). Therefore, a setup for apple orientation on a sorting line has been developed to avoid the presence of stalk or calyx in image by orienting the apples with 97.7% accuracy for 14 different cultivars (Unay et al., 2011). While such a system reduces the number of false positives by avoiding erroneous classification of the stalk or calyx as bruises, it limits bruise detection to the zones around the equator of the fruit. So, bruises on the top and bottom side of the fruit will not be detected by this system.

In order to build a robust apple sorting system which can detect small defects while handling different cultivars, several setups have been proposed using multispectral and hyperspectral imaging (HSI) in the Visible and Near Infrared (Vis-NIR) range (Kleynen et al., 2005; Unay et al., 2011). Using Vis-NIR HSI for model building has been shown to lead to a better detection of bruises in different apple varieties such as Golden Delicious, Jonagold and Braeburn (Ariana & Lu, 2010), as well as other types of food (ElMasry, Wang, Vigneault, Qiao, & ElSayed, 2008; Esquerre, Gowen, O'Donnell, & Downey, 2009; Lin et al., 2003). Since different cultivars have different spectral signatures, a sorting line which can handle multiple cultivars would be very valuable. Moreover, the large number of spectral variables per pixel and the large number of pixels per fruit makes real-time pixel classification based on the full spectrum challenging from a computational point of view. In addition, the lack of clear spectral differences in the visible and very near infrared range (400–1000 nm) between sound and recently bruised tissue gave rather low detection accuracies for fresh bruises (Kavdir & Guyer, 2005; Mehl, Chao, Kim, & Chen, 2002). While promising results for early bruise detection in apples have been reported for Short Wave Infrared (1000–2500 nm SWIR) HSI (Baranowski, Mazurek, Wozniak, & Majewska, 2012; Horabik, Baranowski, & Tys, 2007; Kim et al., 2011), and online Vis-NIR HSI has been demonstrated for industrial applications (Bae, Kim, Kim, & Lee, 2006; Wu et al., 2012), robust industrial SWIR HSI on fruit and vegetables remains challenging. It has also been reported that vis-NIR bruise detection is more challenging in bi-colored apples (Van Zeebroeck et al., 2007). Therefore, the aim of this study was to investigate the potential of SWIR HSI for real-time bruise detection in Jonagold apples, the most important bi-colored apple cultivar in Flanders (VLAM, 2015).

Compared to the Si based sensors used in the 400–1000 nm range, the Indium Gallium Arsenide (InGaAs) and Mercury Cadmium Tellurium (MCT) based focal plane array (FPA) sensors used in SWIR imagers are more sensitive to manufacturing defects, temperature variation and cooling fluctuations, which result in pixel to pixel non uniformity (Parra, Meza, & Torres, 2014). Researchers have investigated non-uniformity compensation (Isoz, Svensson, Renhorn, Box, & Linköping, 2005) for infrared imagers in defense and security applications (Battaglia, Burzi, Moyer, Sudol, & Passe, 2010), involving reference measurements on a large reflectance standard covering the entire field of view. However, the sub-region reflectance calibration methods typically used in food sorting applications using SWIR HSI do not correct for such spatial and spectral non-uniformity as those panels are expensive.

Common broadband illumination within SWIR hyperspectral imaging systems use Halogen spots (Baranowskiet al., 2012; Feng & Sun, 2012; Kim et al., 2011; Xing, Symons, Hatcher, & Shahin, 2011). Those spots are placed empirically around the field of view, not considering the curvature of the samples, thus resulting in limited uniformity. The combination of this poor illumination uniformity with the glossiness of the waxy skin of fruit and vegetables limits the detection accuracy for damaged regions (Huang, Zhang, Li, & Zhang, 2013).

To overcome the above mentioned limitations for SWIR HSI, the added value of optimal homogeneous illumination, pixel based reflectance calibration and glare correction techniques has been investigated in this study. The added value of those techniques is compared on a case study of online early apple bruise detection.

2. Materials and methods

2.1. Apple samples

Thirty Jonagold apples were purchased at a Belgian local supermarket. The apples were first kept at room temperature for 24 h, then imaged before and 2 h after damage. The apples were weighted using a scale (Adventurer Pro, Ohaus, Nänikon, Switzerland). The radius of curvature was measured prior to bruising using a depth gage measurement device (digimatic depth gage 543, Mitutoyo, Chicago, USA), in combination with the following formula (Mohsenin, 1984):

$$R_{x,y} = \frac{(AC)^2}{8(BD)} + \frac{(BD)}{2} \quad (1)$$

where the parameters are defined as illustrated in Fig. 1.

The depth gage with $AC = 19.13\ mm$, was first calibrated on a flat surface such that when the points A, B and C are aligned, with B centered between A and C, the device measures $BD = 0.00\ mm$. The depth gage was then placed on the spot where the apple will be damaged and the depth BD was measured along the meridional (stem-calyx) and equatorial planes of the apple. The derived radii r_x, r_y using (1) were averaged using the harmonic average (Zarifneshat, S. Ghassemzadeh et al., 2010):

$$\mathrm{R} = \frac{2\mathrm{r_x r_y}}{\mathrm{r_x + r_y}} \quad (2)$$

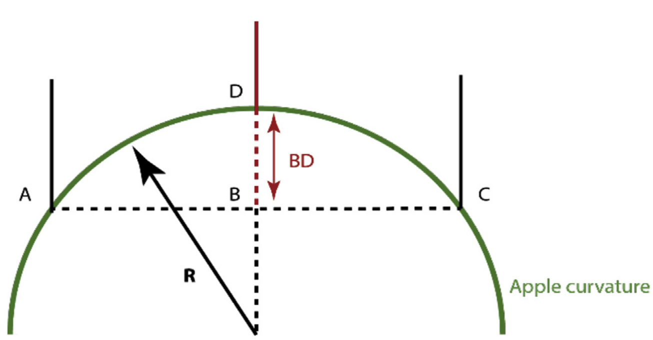

Fig. 1. Radius of curvature measurement. The device consists of two fixed points A and C and one variable point D along the BD axis. When placed on the surface of an apple, the radius of curvature R can be deduced from the distance AC between the two fixed points and the relative distance BD away from the AC segment.