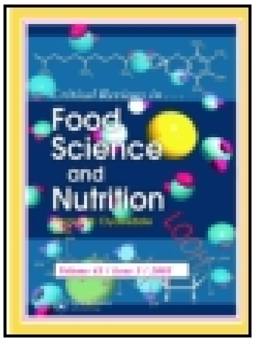


Critical Reviews in Food Science and Nutrition

ISSN: 1040-8398 (Print) 1549-7852 (Online) Journal homepage: http://www.tandfonline.com/loi/bfsn20

Influence of physical and biological variability and solution methods in fruit and vegetable quality non-destructive inspection by using imaging and near-infrared spectroscopy techniques: A review

Baohua Zhang, Dejian Dai, Jichao Huang, Jun Zhou & Qifa Gui

Influence of physical and biological variability and solution methods in fruit and vegetable quality non-destructive inspection by using imaging and near-infrared spectroscopy techniques: A review

Baohua Zhang, Dejian Dai, Jichao Huang, Jun Zhou*, Qifa Gui*

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

*These authors are corresponding authors. Correspondence should be addressed to Jun Zhou (zhoujun@njau.edu.cn) or Qifa Gui (408398424@qq.com). The primary work telephone number is +86 (025) 5860 6714 and fax number is +86 (025) 5860 6585.

ABSTRACT

Over the past decades, imaging and spectroscopy techniques have been rapidly developing and widely applied in non-destructive fruit and vegetable quality assessment. The physical properties (including size, shape, color, position and temperature) and biological properties (including cultivar, season, maturity level and geographical origin) of fruits and vegetables vary from one to another. A great variety of physical and biological properties of agricultural products influence the optical propagation properties and interaction behaviors with incident light, thus decreasing the quality inspection accuracy. Many attempts have been made in image correction and spectral compensation methods to improve the inspection accuracy. This paper gives a detailed summary about influence of physical and biological variability, as well as the correction and compensation methods for eliminating or reducing the effects in fruit and vegetable quality non-destructive inspection by using imaging and spectroscopy techniques. The advantages and disadvantages of the solution methods are discussed and summarized. Additionally, the future challenges and potential trends are also reported.

Keywords

fruits and vegetables, non-destructive inspection, quality, imaging, spectroscopy, physical and biological variability, image correction, spectral compensation

Introduction

Fruits and vegetables are greatly favored by most consumers worldwide because of their vital components such as proteins, vitamins, polysaccharides, phenolics, and minerals (Li et al., 2016a,b,c,d; Tee et al., 2014; Tekaya et al., 2014; Blasco et al., 2007a). Comprehensive quality assessment in fruits and vegetables integrates determination of appearance evaluation and intrinsic characteristics (Pu et al., 2015). External quality attributes are the most important sensory quality indexes of fruits and other agricultural products, external quality can be evaluated according to their visible physical properties, such as size, shape, texture, color, as well as surface defects. The external quality of fruits and vegetables influences their selling price and consumer's purchase behavior (Costa et al., 2011; Zhang et al., 2014a, b, c). Intrinsic characteristics, or internal quality, are invisible but the most important quality attribute of agricultural products, internal quality can be evaluated according to their invisible physical and chemical properties, such as sugar or Soluble Solids Content (SSC), firmness, acidity, ripeness, and so forth (Lorente et al., 2012). The internal quality of agricultural products determines their taste and nutritional value. Imaging and near-infrared spectroscopy techniques, as the two most scientific and efficient noninvasive techniques, have been widely used for fruit and vegetable quality non-destructive inspection and evaluation at the commoditization processing stage.

Imaging techniques have the capability to provide superior spatial information and have been proved to be efficient and scientific tools for quality and safety inspection, classification, and sorting of food and agricultural products (Elmasry et al., 2012; Hu et al., 2016a, b; Huang et al.,

 ACCEPTED MANUSCRIPT

2015; Hu et al., 2015). Imaging techniques include computer/machine vision (CV or MV), hyperspectral/multispectral imaging (HIS/MSI), X-ray imaging (XRI), thermal imaging (TI), ultrasound imaging (UI), fluorescence imaging (FI), and so forth. Machine vision technology is based on color cameras and acquires RGB (red, greed, and blue) images by using three filters to imitate the vision of the human eyes and seek its applications that the human vision system can do (Lorente, et al., 2012; Zhang et al., 2014a). Hyperspectral and multispectral imaging systems integrate both imaging and spectroscopic units into one system to acquire a serial of gray level images at hundreds of thousands of wavelengths at very small intervals. Therefore, the spectral imaging system can provide both the spectral information and spatial information. Each of the other imaging techniques mentioned above has its own individual characteristics. In real world applications, the suitable imaging technique should be determined according to the specific application and their characteristics. More detailed information about emerging imaging techniques can be found in the literature (Chen et al., 2013). Images contain much spatial information (or spectral information for hyperspectral and multispectral images), characters of objects could be described by the features extracted from the images. Once the images have been acquired, inspection tasks become problems of image processing and understanding.

Near-infrared (NIR) spectroscopy technique is based on electromagnetic radiation, and the spectral range is between visible and middle infrared wavelength from 380 to 2500 nm (Li et al., 2016d; Cheng et al., 2013). In near infrared spectroscopy, the product is irradiated with radiation, and then the transmitted, reflected, and interacted radiation could be measured. Transmittance mode measures the NIR spectra that pass through the product, whereas reflectance mode measures the NIR spectral response that reflected from the product. Interactance mode measures the NIR spectral response at laterally separated points on the product surface (Li et al., 2016d). When the NIR radiation penetrates the product, the spectral responses change through wavelength during scattering and absorption processes. The spectral change depends on both the internal chemical composition of the product and the light scattering properties (Nicolai et al., 2007). Therefore, a spectrum can reflect some physical attribute and chemical constitution of the product. After the spectrum is obtained, advanced multivariate statistical techniques, such as partial least squares (PLS) analysis and least squares-support vector machine (LS-SVM) regression, are then used to extract the internal information concerning the chemical components and physical properties (Wang et al., 2015; Dupuy et al., 2010; Elmasry et al., 2007; Fan et al., 2016a,c).

As biological objects growing in the natural environment, fruit external physical properties (including size, shape, color, texture and temperature) and biological properties (including cultivar, season, maturity level and geographical origin) of fruits and vegetables vary from one to another. Physical and biological properties of fruits and vegetables determine the external and internal quality of fruits, in turn, a great variety of physical and biological properties of fruits and vegetables influence the optical propagation properties and interaction behaviors with incident light, thus decreasing the external and internal quality inspection accuracy. Over the past decades, many researchers had made many attempts to eliminate or reduce the effects caused by physical and biological properties in fruit and vegetable quality inspection by using imaging and near-infrared spectroscopy techniques. The solutions, including image correction and spectral compensation methods, can eliminate the effects and improve the inspection accuracy.

Many excellent review papers have been published mainly focused on computer vision, imaging (IE, hyperspectral imaging, multispectral imaging, etc.), and spectroscopy techniques in fruit, vegetable or other agricultural product quality inspection (Blasco et al., 2009; Brosnan and Sun, 2004; Davies, 2009; Lu and Chen, 1999; Narendra and Hareesh, 2010; ElMasry et al., 2007; Liu et al., 2013; Lorente et al., 2012; Li et al., 2014; Wang, et al., 2016; Pu et al., 2015; Feng et al., 2012; ElMasry et al., 2012; Wen et al., 2016; Wang, et al., 2016; Gowen et al., 2007; Cen and He, 2007; Nicolai et al., 2014). A detailed summarization of the influence of physical and biological variability and solution methods in fruit and vegetable quality non-destructive inspection by using imaging and near-infrared spectroscopy techniques is not available. As a result, the main purpose of this paper is to give a comprehensive review about the influence of physical and biological variability, as well as the correction and compensation methods for eliminating or reducing the effects in fruit and vegetable quality non-destructive inspection by using imaging and spectroscopy techniques. The advantage and disadvantage of these solution methods are compared and discussed. Additionally, the challenges and future trends are also reported.

ACCEPTED MANUSCRIPT

Problem description

Effect of geometric (shape and size) variability

In general, most fruits and vegetables, such as apples, citrus fruits, peaches, potatoes, tomatoes and pears, are approximately spherical in geometric appearance. One serious problem for image acquisition of spherical objects is that lighting reflectance is not uniformly distributed (Li et al., 2013b; Huang et al., 2014; Tao, 1996;). The lightness distribution on an object that reaches the Charge Coupled Device (CCD) detector depends on not only the light source position but also the geometrical shape of the object. The basic feature of a spherical fruit image, expressed as $I(x, y)$, captured by an area CCD detector, might be characterized by the following two components (Tao and Wen, 1999): (1) the amount of illumination (expressed as $i(x, y)$) within the field of camera view; and (2) the amount of reflected light rays (expressed as $r(x, y)$) that reaches the CCD camera from the fruit surface. The image $I(x, y)$ could be formed by the following equation:

$$I(x, y) = i(x, y) r(x, y) \quad (1)$$

In real world applications, the illumination of vision lighting system could be considered as uniform in the camera view field. In this situation, the image $I(x, y)$ is just determined by $r(x, y)$, and the Equation (1) could be transformed into:

$$I(x, y) = \mathrm{c} \cdot r(x, y) \quad (2)$$

where c represents the constant illumination component. The reflectance component $r(x, y)$ is mainly governed by the appearance characteristics of inspected object, such as shape, curvature surface, size, color etc. Most fruits and vegetables have spherical shapes. And the spherical surface results in non-uniform reflectance $r(x, y)$ distributed on fruit surface. The reflectance distribution on spherical surface conforms to the rule of curved distributed reflectance, and this means that the position of the inspected fruit having a normal in the direction of the CCD camera presents to be higher intensity than that of the fruits border as showed in Fig. 1(b) (Note that, by contrast, the situation of uniform reflectance of a flat platform is also showed in Fig. 1(a)).

The problem of un-uniform lightness distribution on the fruit and vegetable curved surface exists in almost all the imaging systems, the uneven lightness decreasing the quality inspection accuracy. The un-uniform lightness distribution on the curved surface of fruits and vegetables makes it very difficult to detect the peel defects. Sound tissue with low intensity, especially the region near to the border, might even be wrongly classified as defects. Especially for hyperspectral imaging, the presence of bright spots in the central position caused by over-exposing and progressive darkness of the edges make the problem more serious. The effects caused by spherical also results in increasing the spectral variability, the great variability spectrum increase the complexity of the calibration model while decreasing the universality, practicability and accuracy of the models.

Effect of temperature variability

Fruit and vegetable temperature variations might occur in real world because of changing weather conditions or stored conditioning of the fruit and vegetable after harvest (Peris et al., 2003). The temperature might vary considerable and affect the NIR reflectance spectrum in a non-linear way. The spectrum is sensitive to the sample temperature. The weather conditions and instrument's lamplight can change the sample temperature, thus change the spectra and affect the prediction accuracy (Yao et al., 2013).

Temperature fluctuations are translated through the changes in intermolecular forces to influence of the vibrational spectra (Wulfert et al., 1998). The mechanism of the effect of temperature on NIR spectra is related to the thermal properties of hydrogen bonding (Guo et al., 2016). Due to the existing of a combination of symmetric and antisymmetric stretching modes of water, the hydrogen-bonded OH groups could cause a broad absorption band around 1449 nm (Maeda et al., 1995). The broad band could be viewed as an overlay of five component spectra which might be subject to water clusters with five different hydrogen bonds. The cluster size of hydrogen bonds decreases as the temperature rising, and this would increase the relative absorbance value of the clusters with no hydrogen-bonded OH groups. Consequently, the hydroxyl band of pure water shifts to the lower wavelengths and becomes sharper as the temperature increasing (Peirs et al., 2003a). Hansen et al. (2000) also observed the band shifts in position, as well as the nonlinear changes in absorption values in the OH overtone regions when the temperature of water increasing smaller than 5℃. They also indicted that this problem would arise in any other

 ACCEPTED MANUSCRIPT

products which contain high water level (≥80%). As we known, moisture content of almost all fruits and vegetables is higher than 80%. Therefore, the same problem occurred in fruits and vegetables. Kawano et al. (1995) confirmed the presence of temperature effect on spectral variations and measurements of intact products, and indicated some temperature compensation methods for SSC prediction in peaches.

Temperature variability affects not only the broad absorption band of hydroxyl group in the molecular level, but also the cellular structure of fruit and vegetable tissues in the cellular level. In order to explore the cellular structure of apple tissue and moisture distribution changing caused by temperature raising, images of cellular structure were acquired by Li et al. (2015) by using electron microscope, the microstructure of apple tissue during different temperature was illustrated in Fig. 2. As shown in Fig. 2, the microstructure of apple tissue changes at different temperatures during heating. The radius decrease obviously when temperature was 65℃, these authors indicated that the thermal damage temperature of apple tissues was 65℃. The microstructure of apple tissue shown in Fig. 2 enhance the changes of cellular structure, it is noted that room temperature variability is about -20 to 35℃, thermal damage temperature would not occurred, but the small changes of cellular structure caused by temperature variability is definite. The changes could influence the optical propagation properties and interaction behaviors with incident light, thus decreasing the spectra measurement accuracy.

The influences could be divided into two cases. If the fruit surface temperature is correlated to the response, the trend line joining the actual value to the predicted values presents a slope

ACCEPTED MANUSCRIPT

different from unity. However, if the temperature is not stable, the parasitic information could appear like a noise and results in higher variance of the prediction error (Roger et al., 2003). So, the temperature fluctuations can have effects on both the spectral data acquisition and calibration models in real world applications.

Effect of color variability

The content of chlorophylls, anthocyanins and carotenoids, and their proportion determine fruit and vegetable peel appearance and color (Merzlyak et al., 2003; Abbott, 1999; Saure, 1990) and serve as attributes of quality. Pigments, including chlorophylls, carotenoids and anthocyanins, changes in content occur during their ripening, maturation, storage (Merzlyak et al., 2000; Knee, 1972; Chuma et al., 1981). Pigments play important roles in fruit and vegetable growing and healthcare benefits for humans. Chloroplasts in fruit and vegetable peel contain the major part of fruit and vegetable chlorophylls and carotenoids (Blanke and Lenz, 1989; Merzlyak et al., 2003). Carotenoids are commonly recognized as strong antioxidants. And carotenoids participate in the process of light harvesting (Edge et al., 1997). Anthocyanins determine the peel color of fruits and vegetables. Some literatures also indicated that anthocyanins can protect fruit and vegetable against excessive sun irradiation and harmful UV (Merzlyak et al., 2002; Chalker-Scott, 1999; Smillie and Hetherington, 1999). In addition, the variations of color and spectral reflectance are the main basis for fruit and vegetable grading in commercial inspection systems (Abbott, 1999; Chuma et al., 1981). However, spectra of the absorption coefficient were featured by three main

ACCEPTED MANUSCRIPT

pigments (chlorophyll, carotenoid, and anthocyanin), whereas spectra of the reduced scattering coefficient generally decreased with the increase of wavelength (Qin and Lu, 2008). The average reflectance spectra extracted from ROIs of different peel colors in the apple hyperspectral reflectance images are illustrated in Fig. 3. The average reflectance spectra of different peel colors share the similar trends, but the average spectra of ROIs shifts between different color peel. The reason for spectral variation of ROIs from different color finds their origin in the varying of different reflecting ability and absorbing ability. For example, the spectra from ROIs with green color present a highest reflectance value due to their strong reflecting ability, and the spectra from ROIs with darker color present a relative lower reflectance value due to their weaker reflecting ability.

Obstacles including overlapping light absorption by pigments in fruit peel and the non-linear relationship of the spectral response versus pigment content complicate non-destructive measurement of internal quality attributes, such as SSC, sugar content, acid, and so forth of fruits. The precision of internal quality measured by NIR calibration models is influenced by the contribution of fruit peel pigments to the overall light absorption, which is very difficult to estimate (Guo et al., 2016; Merzlyak et al., 2003). Nevertheless, the peel pigments could be described as spectral perturbation influenced by an absorbance shift (Guo et al., 2016).

Due to the similarity between the true defects and dark color tissues in intensity and texture, the large variety of color of the fruit and vegetable surface also influence the defect recognition and segmentation (Zhang et al., 2014a).

ACCEPTED MANUSCRIPT

Effect of position variability

Fruits and vegetables, as biological objects grown in natural environment, there are main four light conditions: front lighting, back lighting, fruit in the shade and cloudy. The fruit yield was also found to be highly significantly correlated with planting density, canopy cover rate, leaf area index and light intensity in densely planted orchards. Therefore, for an individual fruit or vegetable grown in intensive leaf layers, the main four light conditions might even occur on different parts of one individual fruit or vegetable. Researches have shown that light quality and quantity has effects on fruit or vegetable quality during their growing and ripening stage. Light and shade can influence the activities of sucrose metabolizing enzymes, tissue development, as well as the expression of sucrose synthase-encoding genes of fruits and vegetables, thus they have effects on fruit or vegetable attributes and sugar metabolism (Geromel et al., 2008). The ripening of fruits and vegetables, as well as sugar, anthocyanin, and phenol concentrations, could be markedly reduced by the increasing shade. Conversely, the levels of malic and tartaric acids, titratable acidity, and juice NH_4-N could be increased by shade. The mineral nutrition could also be affected by shade. (Smart et al., 1988). Therefore, the internal quality, such as soluble solid content, sugar content, acidity and firmness, of an individual fruit might vary from one part to another due to position variability and the uneven light exposing and shade in intensive leaf layers. The uneven distribution of internal quality index complicates the fruit and vegetable quality assessment.

A portable spectra-based instrument can be used to inspect the soluble solids content and sugar content over the whole surface of a fruit or vegetable sample with an appropriate distance, which can better estimate the quality-related attributes for fruits or vegetables on trees, or after postharvest. However, for in-line inspection, the measuring position and distance between the detection probe and the fruit or vegetable is random and uncontrollable because of the variations of the fruit or vegetable size, or random posture on the transmission tray. As the near infrared technique can only assess a small part of the each sample, the spatial variability of spectral measurement position and distance should also be taken into account for establishing a robust prediction model for both the portable instruments and in-line inspection systems (Fan et al., 2016b). Fig. 4 shows three separate spectra measured around stem, equator and calyx position. As shown in Fig. 4, the spectra collected from different position share almost the similar peaks, valleys and trends in the same wavelength, but small difference could be also observed. As a result, the spatial position variability of spectral measurement, especially along the distal-proximal (stem-calyx) and axis of a fruit sample might decrease the performance of calibration models (Fan et al., 2016b). It is note that the problem caused by position variability and the uneven distribution of internal quality index could reduce the prediction performance of NIR calibration models. This makes the problem more serious.

 ACCEPTED MANUSCRIPT

Effect of biological variability

Biological characters, such as cultivar, maturity level, geographical origin, season, biological age, of fruits and vegetables have a high variability, even the variation could be observed one to another. Fruit or vegetable composition and concentration are subject to with-in tree variability (spur age, crop load, tree age, position with the tree, location of the tree), orchard variability, biological age variability and seasonal variability (Esti et al., 2002; Peirs et al., 2003b).

Each kind of fruit or vegetable species can have a lot of cultivars. For a specific fruit or vegetable cultivar, the internal quality is influenced by both a large number of genes and surrounding environment. Cultivar variability influence the cellular structure, moisture content, sugar content, and firmness. Consequently, cultivar variability influences the optical propagation properties and interaction behaviors with incident light, such as changing the behaviors of absorption and reflection. Actually, it is clear that cultivar differences are responsible for large amounts of spectral variability (Peris et al., 2003). Thus, cultivar variability increases the complexity of the calibration model while decreasing the universality, practicability and accuracy of the models.

The consumer demands for fruit or vegetable even several months after harvest. Therefore, the harvest is planned before the onset of the climacteric rise (Wills et al., 1998). Maturity level variability influence the fruit or vegetable quality because that the ripening process advanced during postharvest storage with increases in color intensity and decreases in acidity, as well as enhancements in phenolics, anthocyanins, although important differences existed among cultivars (Serrano et al., 2009). Spectral variability caused by maturity level variability certainly would complexity of the calibration model in fruit or vegetable internal quality inspection by using imaging and spectroscopy techniques.

Fruits and vegetables are widely planted all over the world. The appearance quality and internal quality vary due to the origin variability. Origin variability influence the fruit or vegetable internal composition and quality because that soil characteristics, light effects, nutrition, weather condition, as well as growing management are different from orchard to orchard (Fan et al., 2015). Actually, the effect caused by origin variability is relative small, and small different responses of spectrum in the visible and near-infrared region of fruits and vegetables from different orchard are always observed in the real world applications.

Seasonal variability is another important serious factor influencing the spectral variability. The largest source of spectral variation between different fruit or vegetable measurements is caused by the seasonal effect. The reason for seasonal differences finds their origin in the varying of fruit characteristics during different harvest seasons. The sunshine, temperature and precipitation are different in different growing conditions and seasons, so the acid and sugar contents could be different between different seasons, meanwhile, the cell structure, such as cell size, number of cells and amount of intercellular spaces, could also be different between different harvest years (Peris et al., 2003; Bergh, 1985). The large seasonal variability can have great effect on the accuracy of calibration models, since the spectral variation caused by biological variability of future fruits cannot be predicted (Peris et al., 2003).

Other biological variability, such as tree age variability influencing the spectral variability due to the significantly lower cell numbers and smaller cell diameters of younger tree (Marguery and Sangwan, 1993), biological age variability influencing the spectral variability due to the recently harvested fruits are still much firmer than the fruits which have already been stored for a considerable period of time (Bobelyn et al., 2010), are also found in influencing the spectral variability in fruit and vegetable quality non-destructive inspection by using imaging and near-infrared spectroscopy techniques.

Solution methods and applications

Solution methods for geometric variability and applications

One of the main challenges to be faced is related to the challenging problems that arise when the fruits or vegetables to be inspected by using imaging systems have a spherical shape. The two challenging problem is the presence of bright spots in the central position and the darkness of the borders (Lorente et al., 2012). These problems may occur in any types of imaging systems, and have great influence in subsequent classification and inspection tasks.

An apple can be approximately considered as a Lambertian object, and the lightness distribution on the curved surface of the apple is not uniform because of the different reflectance in different position (Zhang et al., 2015a). The non-uniform intensity distribution on the fruit’s image is the main reason resulting in the difficulty and low accuracy of surface defects detection by using a machine vision system. Huang et al. (2012) investigated the lightness distribution on the Lambertian objects, and proposed a spherical intensity transformation method (SITM) to enhance the intensity uniformity of the normal region and kept the low intensity of the defective region in an apple. On this basis, Zhang et al. (2015a) optimized and improved the algorithm by suing open source computer vision (OpenCV). According to the Lambert's law, the intensity I_D of a given point in the curved surface captured by CCD camera could be calculated from the incident light I_L and $\cos\theta$ by using the following equation (Huang et al., 2012):

$$I_D = I_L \cos\theta \quad (3)$$

where θ represents the angle between normal vector of the given point on the curved surface and lines of the given point and the light source. Considering the far greater distance between the inspected object and camera than apple size, the intensity of the incident light I_L could be viewed as uniform on the object surface. Therefore, the uneven intensity distribution is mainly caused by the value of the θ. According to the Equation (3), the position near to the center have a greater value of the θ than the border as showed in Fig. 5(a). Therefore, the position near to the center of the spherical surface presents a higher intensity than the border due to their lower value of the θ. The intensity of the pixels in the annulus area with a radius of r and a width of Δr (marked by A) could be considered as uniform as showed in the Fig. 5(b) (Zhang et al., 2015a).

The average intensity value of the pixels in annulus area A could be calculated according to the following equation (Zhang et al., 2015a ; Huang et al., 2012):

ACCEPTED MANUSCRIPT

$$I_M = \frac{1}{N}\sum_{i \in A} I_i \left(i = 0,1,\cdots,N \right) (4)$$

where I_M represents the average intensity value of pixels in the annulus area A, I_i represents the intensity value of pixel i in the annulus area , and N represents the total number of pixels within the annulus area A.

The lightness correction for the pixels within the annulus area A can be calculated according to the following equation:

$$I_{R_i} = 255 \times \frac{I_i}{I_M} \left(i = 0,1,\cdots,N \right) (5)$$

where I_{R_i} is the lightness of pixel i after lightness correction.

After the lightness correction, the effects influenced by un-uniform lightness distribution on curved surface were dramatically reduced, the pixels in defect candidate regions (including the stems, calyxes and true defects) still keep relative lower intensity value. As a result, the defects could be easily and accurately classified from the corrected images. Fig. 6 shows the segmentation results of the defect candidate regions. Fig. 6(a) is the R component image with background removing extracted from RGB image, and the Fig. 6(b) is the spatial intensity profile for the pixels in the gray line transecting the calyx regions and defect in the uncorrected R component image. As shown in Fig. 6(a) and 6(b), the lightness distribution is not uniform on the curved surface of the apple, the pixels near to the border having a relative lower intensity value than that of the pixels in the central region and the pixels within the stem, calyx regions and

ACCEPTED MANUSCRIPT

defects. Fig. 6(c) shows the defect candidate region recognition results directly segmented from original R channel image in Fig. 6(a). The boundaries of the apples are also added to the defect segmentation images to illustrate the false classification caused by the un-uniform lightness distribution. Fig. 6(d) is corrected image of the R component image, and Fig. 6(e) is the spatial intensity profile for the pixels in the gray line transecting the calyx regions and defect in the corrected image. As shown in Fig. 6 (d) and 6(e), the lightness correction result is encouraging, the intensity value of pixels within sound tissue (including the sound tissue near to edge region) is stretched up to high intensity, and the intensity value of pixels in calyx region and defect still keep relative lower value. Fig. 6(f) shows the defect classification results in corrected R channel image in Fig. 6(d). The results of defect classification in corrected images are reasonably good, especially for the defects near to the border (Zhang et al., 2015a).

The advantage of this method is that the lightness correction method can be automatically conducted adaptive to the fruit size and shape. The performance of the lightness correction is satisfied. However, the method brings another problem that is lower defect detection efficient when the defect candidate region just right in the central of the inspected apple.

Automatic grading of fruits according to surface defects by computer vision systems is very difficult due to the challenge of acquiring images from the curved surface of spherical fruit and the visual similarity between the true defects and the stem-ends (Li et al., 2013b). To eliminate the effect of the uneven lighting distribution on the surface of spherical fruit, Li et al. (2013) proposed a novelty lighting transform method based on a low pass Butterworth filter with a

ACCEPTED MANUSCRIPT

cutoff frequency $D_0 = 7$. Their method successfully converts the non-uniform lightness distribution on spherical oranges into a uniform lightness distribution over the whole fruit surface. Similar to one dimensional signal, low frequencies in images mean pixel values that are changing slowly over space, while high frequency content means pixel values that are rapidly changing in space. Defects on the spherical oranges present relative low intensity compared to the sound tissues nearby, therefore, defects could be viewed as high frequency content in the images. Sound tissues of the oranges present a relative uniform color with the mean pixel values changing slow over space, thus, sound tissues could be viewed as low frequency content. Li et al. (2013) developed lighting mask by using low pass Butterworth filter. The method developed lighting mask by passing signals with a frequency lower than a certain cutoff frequency and attenuates signals with frequencies higher than the cutoff frequency. However, large defects with pixels values changing slowly over space are also low frequency contents in the image, and the edge of oranges which change rapidly in space are high frequency contents in image. So, if the defects are large, the detection efficient would decrease, and the edge of oranges would also be attenuated. But, considering the common defects are relative small and masking processing would be also conducted before correction, the performance of their method is very satisfied. The authors are to be commended on their novelty work. Subsequently, Li et al. (2014) applied their method in color inspection for spherical fruit by using B-spline lighting correction method. It is also should be note that their method is also suitable to the citrus fruits and other uniform agricultural products, such as the apples and other bi-colored fruits, the color variety over space would influence the lighting mask developing.

 ACCEPTED MANUSCRIPT

Influences caused by geometric variability also occur in hyperspectral imaging systems. The images of spherical fruit are much darker in regions near the border than the regions in the central position, and this complicates the process of image and spectral analysis (Gomez-Sanchis et al., 2008). Gomez-Sanchis et al. (2008) proposed a method for correction the adverse effects caused by the curvature of spherical objects in acquiring images with a hyperspectral vision system. They consider the spherical fruit as a Lambertian object and construct a 3D intensity model (intensity distribution model) of the fruit. According to the 3D model, it is possible to obtain the ideal value of the radiation (over the whole surface) that should reach the detector. And it is possible to correct the intensity of the radiation according to the 3D intensity model and make it uniform over the whole surface (no matter where the region locate) of the spherical fruit captured by the detector. The method is been tested using a hyperspectral computer vision system, then each of the pixels in the image can be used to calculate their geometric correction factor. The method has been proved to be effective for eliminating the effects (uneven radiation captured by detector) caused by the various curvatures of spherical fruits (Gomez-Sanchis et al., 2008). The advantage of their method is that the method can homogenize the intensity of the pixels belonging to the same class, no matter where the region of the spherical fruit curvatures are from, meanwhile, the standard deviation between the same class is also reduced. Instead of obtaining the geometric correction factor by interpolation, Zhang et al. (2015a) proposed a lightness correction method by directly obtaining the ideal lightness models according to lightness distribution on ideal spherical object with the same size and shape as the apple fruit. The advantage of Zhang's method is simple and can developed ideal model adaptively to the

ACCEPTED MANUSCRIPT

inspective fruit, but Zhang's method just was applied in single monochromatic image and could facilitate subsequent image-based classification and recognition task, the solutions of spectral influences caused by geometric variability is not mentioned in their work.

Hyperspectral and multispectral scattering are promising techniques for nondestructive inspecting of multiple quality-related attributes of fruits and other agricultural products (Pu et al., 2015; Peng and Lu, 2008). Influences caused by size and shape variability are also observed in hyperspectral and multispectral scattering images. Two types of light intensity distortion could occur to the scattering images due to the curved fruit surface. One is the scattering distance distortion and the other is the scattering intensity distortion. The method presented in Peng and Lu (2006a) was applied to correct distortion caused by shape and size variability of fruits. Fig. 7 shows the actual scattering distance z could be calculated by using Equation (6):

$$z = s \cdot \tan^{-1} \frac{x}{\sqrt{s^2 - x^2}} \quad (6)$$

Where x represents the horizontal linear distance between two points showed in Fig. 7, and s represents the actual radius of the inspected apple. Considering the distance between the inspected fruit and camera is far greater than the imaging field size, and the light rays reaching the detector from fruit curved surface could be approximately viewed as parallel (Peng and Lu, 2007a). However, due to the curvature of the fruit surface, the measured light intensity R_m captured by optical detectors for a point at the curved surface away from the point of light incident tends to underestimate the actual value of light intensity for that point showed in Fig. 7.

According to the Lambertian Consine Law (Qin and Lu, 2009; Kienle et al., 1996), the actual scattering profile at curved surface with scattering medium should be equal to the normal reflectance R. The normal (or corrected) reflectance R showed in Fig. 7 for an arbitrary given point at the spherical fruit surface could be calculated according to Equation (7) (Peng and Lu, 2006a):

$$\mathrm{R} = R_m / \cos\theta = R_m \frac{s}{\sqrt{s^2 - x^2}} \quad (7)$$

where θ represents the angle between the imaging direction and the surface normal. The angle θ changes as the apple size changing. By using their method, the plane scattering distance x and the measured reflectance R_m of each radial circular band could be successfully corrected as circular scattering distance z and the corrected light intensity R. Their method has great potential in eliminating the effects caused by geometric variability, and facilitating the subsequent prediction task in internal quality nondestructive inspection. Qin and Lu (2008) investigated the measurements of optical properties of agricultural products by using spatially resolved hyperspectral diffuse reflectance imaging technique, similar method were used for correcting the size effect of samples.

A good calibration model highly depends on the reliable and accurate spectral measurements (Lorente et al., 2012). Almost all of the literatures about hyperspectral imaging in food quality inspection correct spatial variations of the light and dark current effect of the detectors, however, only a few research papers make attempts to correct the spectral variations caused by the

ACCEPTED MANUSCRIPT

geometrical shape of the spherical fruits, due to the fact that the white reference used in setup is flat, but the fruit inspected is spherical object (Li et al., 2016b; Guo et al., 2015). In order to reduce the spectral variation caused by geometrical shape, Gowen et al. (2008) applied four spectral preprocessing methods, including MSC, MaxN, MedN and MeanN to the spectra of mushroom, and they found that MeanN was the most suitable pretreatment for reducing spectral variability caused by surface curvature (Li et al., 2016b). Li et al. (2016b) applied mean normalization as pretreatment for eliminating the effects caused by curvature in fast detection of early decay in citrus by using reflectance hyperspectral imaging system. Fig. 8(a) confirmed the correction performance of the mean normalization method. The middle picture in Fig. 8(a) is a hyperspectral image of an orange without decay, in order to clearly illustrate the effect of geometrical curvature, spectra was also extracted along the pixel line with 218 pixels. Spectra on the left side are the original spectra directly extracted from the pixel line, the spectra have a serious scattering with CV=0.2559, after correcting, the problem of spectral variations was significantly reduced, the corrected spectra (shown on the right side of Fig. 8(a)) have a scattering with CV=0.0202. It is apparent that the scaling difference in the spectra caused by curvature of orange surface was effectively corrected (Li et al., 2016b). Guo et al. (2015) proposed a method for correcting the light intensity of radiation non-uniform on the apple fruits caused by the curvature of the spherical objects in the process of hyperspectral images acquirement. They corrected the spectra circle by circle by using their method to eliminate the effects caused by the curvature of spherical. Fig. 8(b) shows the performance of the correction method. A conceptual hyperspectral image of apple with nine regions of interest (ROIs) at different locations was shown in the left hand side in Fig. 8(b), the average spectral profiles extracted from the nine ROIs from uncorrected and corrected hyperspectral image were shown in the middle and right hand side in Fig. 8(b). As shown in Fig. 8(b), the spectral variability caused by geometric variability is successfully eliminated (Guo et al., 2015). They applied their method in the visualization of sugar content distribution in apple by using pseudo-color mapping, and better sugar content prediction results could be got from corrected hyperspectral image than that from uncorrected hyperspectral image.

Similar influence of the position in monochromatic images and wavelengths caused by curved surface are almost the same. Therefore, band math between two monochromatic images could also eliminate the effects caused by geometric variability (Zhang et al., 2015a). Additionally, other correction methods, such as multiplicative scatter correction (MSC), Savitzky-Golay smoothing combined with standard normal variate (SNV), smoothing way of moving average, and so forth, are also found in eliminating the influences of geometric variability (Jie et al., 2013; Zhu et al., 2016; Nicolai et al., 2007; Wang et al., 2015). Table 1 shows a detailed summary of studies about solution methods for eliminating the effects caused by geometric variability in fruit and vegetable quality inspection by using imaging and near-infrared spectroscopy techniques.

Solution methods for temperature variability and applications

It is well known that NIR spectrum is sensitive to the variations of temperature. Many published research work have proved a temperature effect on NIR spectra, and proposed different correction or compensation methods to eliminate or reduce the effects caused by temperature variability (Yao et al., 2013; Cozzolino et al., 2007; Xie et al., 2011; Saiz-Abajo et al., 2007; Roger et al., 2003; Chauchard et al., 2004a,b; Nicolai et al., 2007; Peirs et al., 2003a; McGlone et al., 2003).

The correcting strategies for eliminating or reducing the effects of temperature vary depend on availability of the external parameter value. Generally, the situations could be divided into two cases: the temperature is known or unknown beforehand. In the first case, the temperature is known or measured beforehand, two options are possible: (1) priori correction method: the spectrum is corrected as a function of the parameter or the model is determined according to the temperature level; (2) posteriori correction method: the value of the predicted response is corrected on the basis of the temperature level. In the second case, the temperature is unknown, and this is the most common case, two options are also possible reducing the effects of temperature variability: (1) optimization: the calibration sample basis is optimized; (2) preprocessing: the spectrum is preprocessed by using preprocessing method, such as the derivatives, multiplicative scatter correction, standard normal variate (Roger et al., 2003).

Chauchard et al. (2004a,b) presented a brief review of the correction ways in which the models could be corrected for the external factor (temperature) effect and applied them in prediction of soluble solid content. In order to make it clear to the readers, spectral data, or spectral variables, is denoted by $\mathbf{X}$ matrix, and the values to be predicted is denoted by $\mathbf{Y}$ matrix. And $\mathbf{x}$ denote the column of $\mathbf{X}$, transpose notation $\mathbf{x}^T$ denote the row vectors of $\mathbf{X}$, let $\mathbf{b}$ and b_0 be the coefficients calculated for fruits measured at room temperature. Chauchard et al. (2004b) organized into a flow diagram as illustrated in Figure 9. Here, we give a brief summary of the correction methods, and the detailed introduction for external parameter correction could be found in the literature of Chauchard et al. (2004b). They divided the methodologies into two cases: Model corrections and robust calibrations. Case 1: The temperature is known, three correction methods could be conducted for correcting the temperature effect. Method 1.1 develop calibration models which can directly correct the external factors by converting the acquired spectrum **x** into another vector using spectral deformation or matrix concatenation. Method 1.2 reduces the effect of temperature by correcting **b** which is changed using t. The drawback of Method 1.2 is that for different temperature classes, different regression coefficients **b** is needed to be built. Method 1.3 corrects the predicting results by adding a bias value which is determined by the temperature t and the prediction level. Case 2: The temperature is unknown, five correction methods could be conducted for correcting the temperature effect. In this case, the temperature effects could be eliminated by projecting the spectra onto other subspace which is not or less influenced by the temperature variations. Method 2.1 is exhaustive calibration method, and has already been applied to reduce the effects caused by temperature variability and other influence factors. The variations caused by temperature influence are processed by the inverse calibration as the other unknown external effects. Method 2.2 is known as temperature-constrained calibration. A constrained calibration model corrects the temperature effects by developing a two response model which could predict both y and t. The drawback of Method 2.2 is that predicting the value of the variation temperature increases the complexity of the

ACCEPTED MANUSCRIPT

calibration model. Method 2.3 reduces the temperature effects by selecting new variable which could result into a more powerful calibration model. Method 2.4 is known as external parameter orthogonalisation correction method, Method 2.4 supposes the spectral space could project onto three subspaces, and each subspace contains different information which is responding to chemical contents, temperature fluctuation or other rest information. Method 2.5 is self-correction method which aims to correct the temperature effect by intelligent self- adjustment. Subsequently, Chauchard et al. (2004b) applied the above correction methods for soluble solid content prediction. Result shows that multivariate linear regression (MLR) appear to be more robust than partial least square regression (PLSR). And it is possible to establish a robust calibration model which could predict the quantitative value of the influence factor and correct the calibration model itself.

Peirs et al. (2003a) proposed two techniques to eliminate the effect of temperature fluctuations and improve the accuracy of the NIR model for SSC prediction. The first technique is to establish a robust global calibration model to cover the temperature range expected in the future, this technique is also the most practical one in real world applications. The second technique is to develop a serial constant temperature specific calibration models. They pointed that the disadvantage of the second technique is the required training data in calibration step is very large. Result showed that the error on the SSC predicting might be as high as 4% brix without taking any precautions. Roger et al. (2003) proposed a preprocessing method which aims at removing from the $\mathbf{X}$ space the part mostly caused by the external parameter (temperature)

 ACCEPTED MANUSCRIPT

variations. The method estimates this parasitic subspace by computing a PCA on a small set of spectra measured on the same objects. They applied External Parameter Orthogonalisation (EPO) preprocessing in the sugar content measurement of intact apples, and the bias is not more than 0.3° Brix for the same temperature range. Yao et al. (2013) investigated the temperature effect on the SSC of watermelon juice under nine different temperatures increasing from 0℃ to 40℃ at intervals of 5℃, and established local and global compensation models. Results show that the temperature variation can influence the NIR spectra, and the average absorbance changed with the increasing of temperature. The PLSR model developed at 20℃ could perform better than at any other temperatures. And the local models they established were sensitive to the variations of temperature. However, the global model could make temperature variation a negligible interference and show good prediction ability. Banana fruit quality and maturity stages were studied at three different temperatures (20, 25, and 30℃) by using hyperspectral imaging technique in the visible and near infrared (400-1000 nm) regions by Rajkumar et al. (2012). They developed different regression models for the three temperature levels. They found that the changes in total soluble solids and firmness stored at different temperatures during the ripening process followed the polynomial relationships and the change in moisture content followed a linear relationship at different maturity stages. Although several correction methods have been studied, the robustness of the calibration models developed need to be evaluated by the real-world applications in changeable and unmanageable industrial inspection environment.

ACCEPTED MANUSCRIPT

Solution methods for color variability and applications

The color variability changes image and spectral characters by increasing or decreasing the value of image intensity or spectral reflectance (absorption). Therefore, the color variability influences both the defect detection and internal quality inspection.

Sometimes, fruits or vegetables belonging to the same variety have a high rate of texture and color variability that complicates image analysis (Cubero et al., 2011). The automatic grading of apples according to surface defects is still a challenge due to the great variability of the peel color of the bicolor apple variety (Kleynen et al., 2005). The color variability makes the defects poorly contrasted and difficult to recognize and segment. In order to eliminating the effects of color variability, Kleynen et al. (2005) developed a multispectral imaging system to acquire large number of multi-spectral images, and the image data could almost cover the whole color variability of 'Jonagold' apples. They found that images at 750 and 800 nm wavelengths were insensitive to the color variations of the 'Jonagold' apples and could offer a clear contrast between the defective and sound tissue. Supervised techniques orienting towards individual pixels require previous training given by experts in order to classify the color of each pixel as belonging to any of the regions. However, supervised techniques based on individual pixels are sensitive to the color variability. Blasco et al. (2007b) proposed a region-oriented segmentation algorithm solving the problem related to the variability of the natural color of fruit by dividing the surface of fruit to different regions according to their color, and they applied their algorithm in citrus defect detection, 95% of the defects were correctly detected. Band math methods are simple and efficient analytical methods in hyperspectral image processing and spectral analyzing. Band math methods include four basic arithmetical operation, and a combination of subtraction, addition, division and multiplication operations between images at different wavelengths (Zhang et al., 2015c). Due to the similarity of the influence of physical variability in the same position, band math methods can eliminate the effects caused by the noise, non-uniform distribution of lightness and color variability on the fruits. Zhang et al. (2015c) applied the band math methods to the common defects detection in peaches, and satisfied accuracy was got.

The accuracy of internal quality (sugar content, firmness, acid, soluble solid contents) inspection is highly depend on the accuracy and stability of the spectral response. The color of fruit surface can change the spectral response by changing the reflectance and absorption. Therefore, the difference of spectral data might be caused by either internal chemical contents or color. The precision of internal quality determination by spectral reflectance measurement of fruits and vegetables is highly limited by the contribution of peel color to the overall light absorption, which is very difficult to estimate (Merzlyak et al., 2003). In order to eliminate the effect caused by color variability, Guo et al. (2016) proposed a novel color compensation method in non-destructive measurement of SSC in ‘Fuji’ apple fruit by using shortwave and long wave NIR spectroscopy. Fig. 10 shows the main processes for color compensation of calibration models for SSC prediction in apple using NIR spectroscopy. In order to reduce the effect of color variations on SSC prediction model, Guo et al. (2016) built a multivariate regression compensation model by using color space coordinates as input variables combining with the efficient wavelengths selected by SPA. Compared with traditional PLS regression models, the wavelength selection technique combining with color compensation method can significantly improve the accuracy of the calibration model for SSC prediction.

Unlike temperature, color varies largely and randomly on fruit peel, and as external quality, color is the most important sensory quality attributes of fruits and vegetables, the variations of spectral reflectance and color are also the main basis for fruit and vegetable grading in commercial inspection systems (Abbott, 1999; Chuma et al., 1981). Non-destructive measurement of internal quality in apples is immensely complicated by the obstacles including the overlapping light absorption by color, as well as the non-linear relationship of spectral reflectance versus internal chemical contents in the wavebands of strong absorption. Although, color compensation and other correction methods could eliminate the effects of color variability and improve the accuracy of non-destructive methods, further work in these fields still requires a systematic, in-depth comprehensive understanding of biological tissue optical properties to extract quantitative or qualitative information from nondestructive spectral measurements (Merzlyak et al., 2003).

Solution methods for position variability and applications

The position variability (including the detection position and distance variability between fruit and inspection instrument) of spectrum measurement, especially along the distal-proximal (stem-calyx) and axis within an individual fruit could decrease the prediction accuracy of the calibration model (Fan et al., 2016b; Liu, 2006; Fu, 2008).

For in-line detection, the detection position is random and unknown beforehand. Priori correction and posteriori correction methods conducted on spectrum are not available due to the effect caused by the random position is difficult to estimate. Therefore, in this situation the only solution method is to build a so-called “robust model” by optimizing the calibration sample basis or using preprocessing methods. In order to eliminate the effect of position variability, Cayuela (2008) developed three calibration models for SSC measurement based on different fruit sets. The first calibration was performed with four measures by spectrum, acquired at four 90° equatorial positions, whereas the second and third calibrations were obtained with two 180° equatorial measures by spectrum. The satisfied prediction accuracy was obtained. However, four measures or two measures increase the data acquiring and analyzing time, and thus decrease the efficient of the algorithm. In the application of non-destructive measurement of tomato ‘Heatwave’ (Lycopersicum esculentum) quality attributes by using visible/near infrared spectrometric technique, Shao et al. (2007) took three reflection measurements (350-2500 nm) at three equidistant positions around the equator (approximately 120°) of each tomato. Average spectra reflectance for each tomato was extracted as the average of spectra collected for three positions around the fruit equator. Averaging the spectra reflectance of many measures could be used for reducing the influence of spatial position variability and improving the prediction accuracy, the only drawback might be the complicated process and low efficiency. Fan et al. (2016b) studied the effect of variability of the spectral measurement position on the NIR spectroscopy measurement of SSC of ‘Fuji’ apple fruit. They developed local position models for each measurement position and global position models for the full spectral data collected

 ACCEPTED MANUSCRIPT

from three positions by using PLS. Their research proved that the position variability could influence the prediction performance of calibration models. Local position models were developed with a calibration set at three independent positions at stem, equator and calyx. In order to verify the position variability effect, the local position models were validated with the spectral data sets collected at other positions. Higher RMSEP and lower r_p values when the local position model was applied to predict the soluble solid content of spectra collected at the other position implied existence of effect of position variability. In order to reduce the effect of position variation, the global model was also established by Fan et al. (2016b). The calibration set in the global position model contained of three calibration sets of all positions. CARS method was also applied for efficient wavelengths (EWs) selection. The overall accuracy indicated that the combining of efficient wavelength selection method and global position model could make the variation of spectral measurement position a negligible interference for soluble solid content prediction.

Except the effect of the variation of the measurement position, the distance between detector and sample is another factor that should be taken into consideration for establishing a robust NIR model for internal quality attributes inspection of fruits and vegetables. However, very little literature has focused on this problem in fruit and vegetable quality non-destructive inspection areas.

ACCEPTED MANUSCRIPT

Solution methods for biological variability and applications

Biological characteristics of fruits and vegetables, which are subject to cultivar, harvesting season, geographical origin and maturity level, influence light scatting and absorption. Spectrum changes as biological characteristics changing. Therefore, spectral data could be used to classify the fruits according to a given variability (i.e. varieties, maturity levels, geographic origin, etc.) (Camps and Christen, 2009). In turn, fruit and vegetable cultivar, origin, harvest season and maturity level could also play an important role in the robustness of NIRS models (Bobelyn et al., 2010).

Spectrum varies greatly across different cultivars of fruits and vegetables (Nicolaï et al., 2005; Bassanezi et al., 2009). FT-NIR reflectance spectroscopy technology was applied with the spectral range of 800 nm to 2700 nm to establish multivariate calibration models for TSS, TA, firmness, sugar-to-acid ratio and weight prediction in three cultivars and a multi-cultivar model (Louw and Theron, 2010). Cultivar-specific prediction models for all cultivars were developed respectively. Meanwhile, multi-cultivar calibration model with high robustness was also developed by combining more data for each cultivar at two different harvest years (2007 and 2008 seasons). When the three cultivars are combined into one multi-cultivar calibration model the prediction accuracy improved significantly for both the calibration models and validation models although the error of prediction is high. Interestingly, they found that when considering the relative stable prediction performance of the multi-cultivar calibration models compared to the specific-cultivar calibration models, it is evident that including more cultivar and seasonal variability into a global (multiple) calibration model can improve the robustness and predictability of calibration models for future sample inspection (Louw and Theron, 2010). Jha et al. (2012) conducted a study to evaluate the potential of NIR spectroscopy in the wavelength range of 1200-2200 nm for determining total soluble solids and pH for seven major cultivars of mangoes from seven states of India. In order to reduce the effects caused by cultivar variability, preprocessing technologies (baseline correction, smoothening, multiplicative scatter correction (MSC) and second order derivatisation) were employed in the NIR models developed based on multiple-linear regression (MLR) and partial least square (PLS) regression. The satisfied performance indicated the NIRS potential to predict internal quality parameters of major cultivars of mangoes non-destructively for both models. Penchaiya et al. (2009) investigated the potential of near infrared spectroscopy over the range of 780 nm to 1690 nm to measure the soluble solid contents and firmness of bell pepper. They established PLS calibration models by using a large calibration set which contained data from two different cultivars and two different harvest seasons. In order to developed robustness model, Savitzky-Golay second derivative and EMSC (extended multiplicative signal correction) methods were also employed as preprocessing methods. The satisfactory prediction accuracy indicated that NIR spectroscopy and Savitzky-Golay second derivative preprocessing could be used as an efficient technique for non-destructive measuring the soluble solid contents in bell pepper. In order to increase the robustness of calibration models, they believe it is necessary to have sufficient variability in the calibration set.

 ACCEPTED MANUSCRIPT

Spectral variations caused by the biological variability of fruit or vegetable samples from different orchards and seasons indicate that future fruits and vegetables could not be measured or predicted with high accuracy by using the current models without updates (Magwaza et al., 2014; Peris et al., 2003). Magwaza et al. (2014) conducted a study to investigate the performance of PLS calibration models established based on data from individual orchards and PLS models established based on combined orchards at two different harvesting seasons in predicting rind physic-chemical attributes of mandarin fruit. To prove the presence of the effect of season variability on PLS model prediction performance, specific calibration models were established using fruits from the 2012 harvest season and validated using the data from the 2011 harvest season. Results with very low prediction accuracy indicate that the seasonal variation significantly affects calibration models across seasons. In order to reduce the effects caused by seasonal and origin variability, Magwaza et al. (2014) developed robust models combining two harvest seasons and four different orchards. The robust model incorporating more orchards and harvest seasons could gave better prediction accuracy for all quality attributes compared to specific models developed based on a single orchard or single harvest season. Combinations of spectral pretreatments such as SNV or MSC can also reduce the effects of different harvest years by minimizing baseline offset and variation of intensity due to seasonal differences (Magwaza et al., 2014; Li et al., 2013a; Bobelyn et al., 2010). The effects of fruit geographical origin and planting area on calibration model robustness were observed and proved by Bobelyn et al. (2010) in sugar content prediction by using NIR spectroscopy. Sugar content prediction accuracy could

ACCEPTED MANUSCRIPT

be significantly improved by using a model developed from data collected over three origins compared to calibration models developed using a single or combined two origin data.

Additionally, maturity levels could change physical and chemical attributes of the fruits or vegetables. Thus result in differences in spectral behaviors. Munera et al. (2017) conducted a study to evaluate the usefulness of hyperspectral imaging in the 460-1020 nm range as a non-destructive tool to assess the astringency of persimmon at three different stages of commercial maturity levels. In order to reduce the effects of maturity levels, data collected from each maturity stage were used to build the models and a pre-processing standard normal variate (SNV) was also applied to the spectra in order to remove scatter effects from the original spectral data. The model with the R_P^2 of 0.91 indicated that the hyperspectral imaging is a promising technology to assess the astringency of persimmon.

The ultimate aim of any calibration model is to be robust and universal. Therefore, it is necessary and important to emphasize that more new variability should be included for developed more robust models in predicting future samples from different cultivars, geographical origins, harvesting seasons and/or maturity levels (Magwaza et al., 2014). With NIR analyses, the calibration set need be sufficiently rich in variability and should include samples from diverse cultivars, geographical origins, harvesting seasons and maturity levels to confirm their predictive performance and overall robustness (Pissard et al., 2012; Wedding et al., 2011; Peirs et al., 2002; Wang et al., 2016; Lin and Ying, 2009; Wedding et al., 2013; Nicolaï et al., 2005; McGlone et al., 2003; Liu et al., 2015). Meanwhile, the calibration models should also be updated for every

 ACCEPTED MANUSCRIPT

different condition, including season, variety, maturity level and origin. With the increasing number of calibration samples and of different conditions, the robustness of the calibration model increases (ZerbinI et al., 2006). Table 2 shows a detailed summary of studies about solution methods for eliminating the effects caused by biological variability in fruit and vegetable quality inspection by using imaging and near-infrared spectroscopy techniques.

Challenges and future trends

Imaging and near-infrared spectroscopy techniques are powerful tools for the non-destructive sensing of multiple quality and safety attributes of agricultural products and food. However, as natural biological objects, fruits and vegetables have various physical and biological characters. The physical and biological variability of fruits and vegetables could have great influence on the inspection accuracy of imaging and near-infrared spectroscopy techniques.

The physical variability (including geometric (size and shape) variability, color variability) influences the lightness distribution on the curved surface of fruits and vegetables. The uneven intensity distribution on curved surface increases the difficulty of external quality inspection (especially the defects detection) of fruits and vegetables. Although various attempts have been made for lightness correction and satisfied performance is got, the accurate judgment of the size of defects on curvature surface and slight defect detection are still challenges in real world applications.

The biological variability (including cultivar, harvesting season, geographical origin and maturity level variability) and physical variability (including temperature variability, position variability, color variability) can influence the optical propagation properties and interaction behaviors with incident light, thus decreasing the internal quality inspection accuracy of fruits and vegetables. Various compensation and correction methods have been conducted both on the spectrum and calibration models and improved accuracy is got, there is still lots of problems need to be solved. Updating the calibration models with more new variability in the calibration set could improve the predictability and robustness of future samples but in other hand it also increases the complexity of the calibration model. Calibration models with much more variability could even decrease the universality, practicability and accuracy of the models sometimes. Viewed in terms of game theory, the balance between specificity and universality of models should be paid more attention to. Whatever, one thing is certain, that is when you want to get higher inspection accuracy for one cultivar fruit harvested at one season and orchard, specific models is the best selection, but when you want to make the models robust for more cultivars, seasons and origins, global models with more variability should be selected.

Though many solutions have been presented to reduce the effects caused by physical and biological variability in fruit and vegetable quality non-destructive inspection by using imaging and near-infrared spectroscopy techniques in previous studies by the scientific researchers worldwide, in order to realize in-line of fast non-destructive inspection or grading, there is a long way to go. The mechanism of the optical propagation or interaction in/with biological objects, solutions for some effects caused by physical and biological variability off-line and in-line, as well as transformation of the solutions and calibration models are needed to be investigated next.

Conclusions

During the past decades, imaging and near-infrared spectroscopy techniques have been widely used in the non-destructive inspection the quality and safety of fruits and vegetables, and been proven to be scientific tools for efficient and reliable measurement in food industry. This review provide a summary about influence of physical and biological variability and solution methods in fruit and vegetable quality non-destructive inspection by using imaging and near-infrared spectroscopy techniques. The physical variability, including geometric (size and shape) variability, temperature variability, color variability and position variability, of fruits and vegetables was detailed analyzed, the way they influence the computer vision system, hyperspectral imaging system and other image-based system was also analyzed. The correction methods for eliminating the influence of physical variability were detailed summarized. The biological variability, including the cultivar variability, harvesting season variability, geographical origin variability and maturity level variability, was detailed presented. The way they influence the internal biological characteristics, physical and chemical properties, optical properties, as well as interaction behaviors with incident light was also analyzed. The compensation and correction methods for eliminating influence of biological variability and improving the robust of the models were detailed summarized. The advantages and disadvantages of the solutions are discussed and summarized. Additionally, the future challenges and potential trends are also reported.

Acknowledgments

This work was supported by the National Natural Science Foundation of China (project No. 31471419) and Young Scientist Fund of National Natural Science Foundation of China (project No. 11604154). The authors also wish to thank Dr. Jiangbo Li, Dr. Shuxiang Fan from Beijing Research Center of Intelligent Equipment for Agriculture, Dr. Zhiming Guo from Jiangsu University, Dr. Xingshu Li from Northwest A&F University for providing original figures.

ACCEPTED MANUSCRIPT

References

Abbott, J.A. (1999). Quality measurement of fruits and vegetables. *Postharvest Biology & Technology*. **15**: 207-25.

Bassanezi, R.B., Montesino, L.H.and Stuchi, E.S. (2009). Effects of huanglongbing on fruit quality of sweet orange cultivars in Brazil. *European Journal of Plant Pathology*. **125**: 565-72.

Beghi, R., Spinardi, A., Bodria, L., Mignani, I.and Guidetti, R. (2013). Apples Nutraceutic Properties Evaluation Through a Visible and Near-Infrared Portable System. *Food and Bioprocess Technology*. **6**: 2547-54.

Bergh, O. (1985). Effect of the previous crop on cortical cell number of Malus domestica cv. Starking Delicious apple flower primordia, flowers and fruit. *South African Journal of Plant & Soil*.**2**: 191-6.

Blanke, M.and Lenz, F. (1989). Fruit photosynthesis. *Plant, Cell & Environment*. **12**: 31-46.

Blasco, J., Aleixos, N., Cubero, S., Juste, F., Gómez-Sanchis, J., Alegre, V.and Moltó, E. (2009). Computer vision developments for the automatic inspection of fresh and processed fruits. *Image Analysis for Agricultural Products and Processes, ISSN*. 0947-7314.

Blasco, J., Aleixos, N., Gómez, J.and Moltó, E. (2007a). Citrus sorting by identification of the most common defects using multispectral computer vision. *Journal of Food Engineering*. **83**: 384-93.

Blasco, J., Aleixos, N.and Molto, E. (2007b). Computer vision detection of peel defects in citrus by means of a region oriented segmentation algorithm. *Journal of Food Engineering*. **81**: 535-43.

Blasco, J.and Moltó, E. Identification of defects in citrus skin using multispectral imaging; proceedings of the International conference on agricultural engineering, AgEng, F, 2002 [C].

Bobelyn, E., Lammertyn, J., Nicolai, B.M., Saeys, W., Serban, A.S.and Nicu, M. (2010). Postharvest quality of apple predicted by NIR-spectroscopy: Study of the effect of biological variability on spectra and model performance. *Postharvest Biology & Technology*. **55**: 133-43.

Brosnan, T.and Sun, D.-W. (2004). Improving quality inspection of food products by computer vision—a review. *Journal of Food Engineering*. **61**: 3-16.

Bureau, S., Ruiz, D., Reich, M., Gouble, B., Bertrand, D., Audergon, J.-M.and Renard, C.M. (2009). Rapid and non-destructive analysis of apricot fruit quality using FT-near-infrared spectroscopy.*Food Chemistry*. **113**: 1323-8.

Buyukcan, M.B.and Kavdir, I. (2016). Prediction of some internal quality parameters of apricot using FT-NIR spectroscopy.

Cabezasserrano, A.B., Amodio, M.L., Cornacchia, R., Rinaldi, R.and Colelli, G. (2009). Suitability of five different potato cultivars (Solanum tuberosum L.) to be processed as fresh-cut products.*Postharvest Biology & Technology*. **53**: 138-44.

Camps, C.and Christen, D. (2009). Non-destructive assessment of apricot fruit quality by portable visible-near infrared spectroscopy. *LWT - Food Science and Technology*. **42**: 1125-31.

Cayuela, J.A. (2008). Vis/NIR soluble solids prediction in intact oranges (Citrus sinensis L.) cv. Valencia Late by reflectance. *Postharvest Biology & Technology*. **47**: 75-80.

Cen, H.and He, Y. (2007). Theory and application of near infrared reflectance spectroscopy in determination of food quality. *Trends in Food Science & Technology*. **18**: 72-83.

Chalker-Scott, L. (1999). Environmental significance of anthocyanins in plant stress responses. *Photochemistry and photobiology*. **70**: 1-9.

Chauchard, F., Cogdill, R., Roussel, S., Roger, J.M., Bellon-Maurel, V.and Cogdill, R. (2004a). Application of LS-SVM to non-linear phenomena in NIR spectroscopy: development of a robust and portable sensor for acidity prediction in grapes. *Chemometrics & Intelligent Laboratory Systems*. **71**: 141-50.

Chauchard, F., Roger, J.and Bellonmaurel, V. (2004b). Correction of the temperature effect on near infrared calibration-application to soluble solid content prediction. *Journal of Near Infrared Spectroscopy*. **12**: 199-205.

Chen, Q., Zhang, C., Zhao, J.and Ouyang, Q. (2013). Recent advances in emerging imaging techniques for non-destructive detection of food quality and safety. *TrAC Trends in Analytical Chemistry*.**52**: 261-74.

Cheng, J.-H., Dai, Q., Sun, D.-W., Zeng, X.-A., Liu, D.and Pu, H.-B. (2013). Applications of non-destructive spectroscopic techniques for fish quality and safety evaluation and inspection. *Trends in food science & technology*. **34**: 18-31.

Cheng, J. H., and Sun, D. W. (2015). Recent applications of spectroscopic and hyperspectral imaging techniques with chemometric analysis for rapid inspection of microbial spoilage in muscle foods. Comprehensive Reviews in Food Science and Food Safety. **14(4)**, 478-490.

Chuma, Y., Uchida, S., Shemsanga, K.H.H.and Matsuoka, T. (1981). Bulk Physical and Thermal Properties of Cereal Grains as Affected by Moisture Content. *Journal of the Faculty of Agriculture Kyushu University*. **26**: 57-70.

Cortés, V., Ortiz, C., Aleixos, N., Blasco, J., Cubero, S.and Talens, P. (2016). A new internal quality index for mango and its prediction by external visible and near-infrared reflection spectroscopy. *Postharvest Biology & Technology*. **118**: 148-58.

Costa, F., Cappellin, L., Longhi, S., Guerra, W., Magnago, P., Porro, D., Soukoulis, C., Salvi, S., Velasco, R.and Biasioli, F. (2011). Assessment of apple (Malus× domestica Borkh.) fruit texture by a combined acoustic-mechanical profiling strategy. *Postharvest biology and technology*. **61**: 21-8.

Cozzolino, D., Liu, L., Cynkar, W.U., Dambergs, R.G., Janik, L., Colby, C.B.and Gishen, M. (2007). Effect of temperature variation on the visible and near infrared spectra of wine and the consequences on the partial least square calibrations developed to measure chemical composition. *Analytica Chimica Acta*. **588**: 224-30.

Cubero, S., Aleixos, N., Moltó, E., Gómez-Sanchis, J.and Blasco, J. (2011). Advances in Machine Vision Applications for Automatic Inspection and Quality Evaluation of Fruits and Vegetables. *Food and Bioprocess Technology*. **4**: 487-504.

Dai, Q., Cheng, J.H., Sun, D.W.and Zeng, X.A. (2015). Advances in Feature Selection Methods for Hyperspectral Image Processing in Food Industry Applications: A Review. *Critical Reviews in Food Science and Nutrition*. **55**: 1368-82.

Davies, E. (2009). The application of machine vision to food and agriculture: a review. *The Imaging Science Journal*. **57**: 197-217.

Oliveira, G.A., Bureau, S., Renard, C.M., Pereira-Netto, A.B.and De, C.F. (2014). Comparison of NIRS approach for prediction of internal quality traits in three fruit species. *Food Chemistry*.**143**: 223-30.

Deak, K.J., Szigedi, T., Palotas, G., Daood, H.G.and Helyes, L. (2014). Determination of °Brix, lycopene, β-carotene and total carotenoid content of processing tomatoes using near infrared spectroscopy. *Acta Horticulturae*. **1081**: 63-7.

Dupuy, N., Galtier, O., Le Dréau, Y., Pinatel, C., Kister, J.and Artaud, J. (2010). Chemometric analysis of combined NIR and MIR spectra to characterize French olives. *European journal of lipid science and technology*. **112**: 463-75.

Edge, R., Mcgarvey, D.and Truscott, T. (1997). The carotenoids as anti-oxidants—a review. *Journal of Photochemistry and Photobiology B: Biology*. **41**: 189-200.

Elmasry, G., Cubero, S., Moltó, E.and Blasco, J. (2012). In-line sorting of irregular potatoes by using automated computer-based machine vision system. *Journal of Food Engineering*. **112**: 60-8.

Elmasry, G., Wang, N., Elsayed, A.and Ngadi, M. (2007). Hyperspectral imaging for nondestructive determination of some quality attributes for strawberry. *Journal of Food Engineering*. **81**: 98–107.

Esti, M., Cinquanta, L., Sinesio, F., Moneta, E.and Di Matteo, M. (2002). Physicochemical and sensory fruit characteristics of two sweet cherry cultivars after cool storage. *Food Chemistry*. **76**: 399-405.

Fan, S., Guo, Z., Zhang, B., Huang, W.and Zhao, C. (2016a). Using Vis/NIR Diffuse Transmittance Spectroscopy and Multivariate Analysis to Predicate Soluble Solids Content of Apple. *Food Analytical Methods*. **9**: 1333-43.

Fan, S., Huang, W., Guo, Z., Zhang, B., Zhao, C., and Qian, M. (2015). Assessment of Influence of Origin Variability on Robustness of Near Infrared Models for Soluble Solid Content of Apples. Chinese Journal of Analytical Chemistry. 2015, 43(2):239-244.

 ACCEPTED MANUSCRIPT

Fan, S., Zhang, B., Li, J., Huang, W.and Wang, C. (2016b). Effect of spectrum measurement position variation on the robustness of NIR spectroscopy models for soluble solids content of apple.*Biosystems Engineering*. **143**: 9-19.

Fan, S., Zhang, B., Li, J., Liu, C., Huang, W.and Tian, X. (2016c). Prediction of soluble solids content of apple using the combination of spectra and textural features of hyperspectral reflectance imaging data. *Postharvest Biology & Technology*. **121**: 51-61.

Feng, Y.Z. and Sun, D.W. (2012). Application of hyperspectral imaging in food safety inspection and control: a review. *Critical Reviews in Food Science and Nutrition*. **52**: 1039-58.

Fu, X. (2008). Nondestructive detection of fruit internal quality based on visible and near infrared spectroscopy (Ph.D Thesis). Zhejiang University. pp. 105–108.

Geromel, C., Ferreira, L.P., Davrieux, F., Guyot, B., Ribeyre, F., Brígida, D.S.S.M., Protasio Pereira, L.F., Vaast, P., Pot, D.and Leroy, T. (2008). Effects of shade on the development and sugar metabolism of coffee (Coffea arabica L.) fruits. *Plant Physiology & Biochemistry*. **46**: 569-79.

Gomezsanchis, J., Molto, E., Campsvalls, G., Gomezchova, L., Aleixos, N.and Blasco, J. (2008). Automatic correction of the effects of the light source on spherical objects. An application to the analysis of hyperspectral images of citrus fruits. *Journal of Food Engineering*. **85**: 191-200.

Gómez-Sanchis, J., Moltó, E., Camps-Valls, G., Gómez-Chova, L., Aleixos, N.and Blasco, J. (2008). Automatic correction of the effects of the light source on spherical objects. An application to the analysis of hyperspectral images of citrus fruits. *Journal of food engineering*. **85**: 191-200.

Gowen, A., O'donnell, C., Taghizadeh, M., Cullen, P., Frias, J.and Downey, G. (2008a). Hyperspectral imaging combined with principal component analysis for bruise damage detection on white mushrooms (Agaricus bisporus). *Journal of Chemometrics*. **22**: 259-67.

Gowen, A.A., O'donnell, C.P., Cullen, P.J., Downey, G.and Frias, J.M. (2007). Hyperspectral imaging – an emerging process analytical tool for food quality and safety control. *Trends in Food Science & Technology*. **18**: 590-8.

Gowen, A.A., O'donnell, C.P., Taghizadeh, M., Cullen, P.J., Frias, J.M.and Downey, G. (2008b). Hyperspectral imaging combined with principal component analysis for bruise damage detection on white mushrooms (Agaricus bisporus) (pages 259–267). *Journal of Chemometrics*. **22**: 259–67.

Guo, Z., Huang, W., Peng, Y., Chen, Q., Ouyang, Q.and Zhao, J. (2016). Color compensation and comparison of shortwave near infrared and long wave near infrared spectroscopy for determination of soluble solids content of ‘Fuji’ apple. *Postharvest Biology & Technology*. **115**: 81-90.

Guo, Z., Zhao, C., Huang, W., Peng, Y., Li, J., and Wang, Q. (2015). Intensity correction of visualized prediction for sugar content in apple using hyperspectral imaging. Nongye Jixie Xuebao/transactions of the Chinese Society of Agricultural Machinery. 46(7), 227-232.

Guthrie, J.A., Liebenberg, C.J.and Walsh, K.B. (2006). NIR model development and robustness in prediction of melon fruit total soluble solids. *Australian Journal of Agricultural Research*. **57**: 411-8.

Guthrie, J.A., Reid, D.J.and Walsh, K.B. (2005a). Assessment of internal quality attributes of mandarin fruit. 2. NIR calibration model robustness. *Australian Journal of Agricultural Research*. **56**: 417-26.

Guthrie, J.A., Walsh, K.B., Reid, D.J.and Liebenberg, C.J. (2005b). Assessment of internal quality attributes of mandarin fruit. 1. NIR calibration model development. *Australian Journal of Agricultural Research*. **56**: 417-26.

Hansen, W., Wiedemann, S., Sneider, M.and Wortel, V. (2000). Tolerance of near infrared calibrations to temperature variations; a practical evaluation. *Journal of Near Infrared Spectroscopy*. **8**: 125-32.

Hu, M.H., Dong, Q.L.and Liu, B.L. (2016a). Classification and characterization of blueberry mechanical damage with time evolution using reflectance, transmittance and interactance imaging spectroscopy. *Computers & Electronics in Agriculture*. **122**: 19-28.

 ACCEPTED MANUSCRIPT

Hu, M.H., Dong, Q.L., Liu, B.L.and Opara, U.L. (2016b). Prediction of mechanical properties of blueberry using hyperspectral interactance imaging. *Postharvest Biology & Technology*. **115**: 122-31.

Hu, M.H., Dong, Q.L., Liu, B.L., Opara, U.L.and Chen, L. (2015). Estimating blueberry mechanical properties based on random frog selected hyperspectral data. *Postharvest Biology & Technology*.**106**: 1-10.

Huang, W., Li, J., Wang, Q.and Chen, L. (2015). Development of a multispectral imaging system for online detection of bruises on apples. *Journal of Food Engineering*. **146**: 62-71.

Huang, W., Li, J., Zhang, C., Li, B., Chen, L., and Zhang, B. (2012). Detection of surface defects on fruits using spherical intensity transformation. Nongye Jixie Xuebao/transactions of the Chinese Society of Agricultural Machinery. 43(12), 187-191.

Jha, S.N.and Garg, R. (2010). Non-destructive prediction of quality of intact apple using near infrared spectroscopy. *Journal of Food Science and Technology*. **47**: 207-13.

Jha, S.N., Jaiswal, P., Narsaiah, K., Gupta, M., Bhardwaj, R.and Singh, A.K. (2012). Non-destructive prediction of sweetness of intact mango using near infrared spectroscopy. *Scientia Horticulturae*. **138**: 171–5.

Jie, D., Xie, L., Fu, X., Rao, X.and Ying, Y. (2013). Variable selection for partial least squares analysis of soluble solids content in watermelon using near-infrared diffuse transmission technique. *Journal of Food Engineering*. **118**: 387-92.

Kawano, S., Abe, H.and Iwamoto, M. (1995). Development of a calibration equation with temperature compensation for determining the Brix value in intact peaches. *Journal of Near Infrared Spectroscopy*. **3**: 211.

Kienle, A., Lilge, L., Patterson, M.S., Hibst, R., Steiner, R.and Wilson, B.C. (1996). Spatially resolved absolute diffuse reflectance measurements for noninvasive determination of the optical scattering and absorption coefficients of biological tissue. *Applied Optics*. **35**: 2304-14.

Kleynen, O., Leemans, V.and Destain, M.F. Development of a multi-spectral vision system for the detection of defects on apples [M]. John Wiley & Sons, Ltd, 2005.

Knee, M. (1972). Anthocyanin, Carotenoid, and Chlorophyll Changes in the Peel of Cox's Orange Pippin Apples during Ripening on and off the Tree. *Journal of Experimental Botany*. **23**: 184-96.

Leemans, V., Magein, H.and Destain, M.F. (1998). Defects segmentation on 'Golden Delicious' apples by using colour machine vision. *Computers & Electronics in Agriculture*. **20**: 117-30.

Li, J., Chen, L., Huang, W., Wang, Q., Zhang, B., Tian, X., Fan, S.and Li, B. (2016a). Multispectral detection of skin defects of bi-colored peaches based on vis–NIR hyperspectral imaging.*Postharvest Biology & Technology*. **112**: 121-33.

Li, J., Huang, W.and Guo, Z. Detection of defects on apple using B-spline lighting correction method; proceedings of the International Conference on Photonics and Image in Agriculture Engineering, F, 2013 [C].

Li, J., Huang, W., Tian, X., Wang, C., Fan, S., and Zhao, C. (2016b). Fast detection and visualization of early decay in citrus using Vis-NIR hyperspectral imaging. Computers and Electronics in Agriculture. 127, 582-592.

Li, J., Huang, W., Zhao, C. and Zhang, B. (2013a). A comparative study for the quantitative determination of soluble solids content, pH and firmness of pears by Vis/NIR spectroscopy. *Journal of Food Engineering*. **116**: 324-32.

Li, J., Rao, X., Wang, F., Wu, W.and Ying, Y. (2013b). Automatic detection of common surface defects on oranges using combined lighting transform and image ratio methods. *Postharvest Biology & Technology*. **82**: 59-69.

Li, J., Rao, X.and Ying, Y. (2011). Detection of common defects on oranges using hyperspectral reflectance imaging. *Computers & Electronics in Agriculture*. **78**: 38-48.

Li, J., Tian, X., Huang, W., Zhang, B.and Fan, S. (2016c). Application of Long-Wave Near Infrared Hyperspectral Imaging for Measurement of Soluble Solid Content (SSC) in Pear. *Food Analytical Methods*. 1-12.

Li, J.B., Huang, W.Q.and Zhao, C.J. (2014). Machine vision technology for detecting the external defects of fruits — a review. *Imaging Science Journal the*. **63**: 241-51.

Li, J. B., Rao, X. Q., Ying, Y. B., Ma, B. X., and Guo, J. X. (2009). Background and external defects segmentation of navel orange based on mask and edge gray value compensation algorithm. Nongye Gongcheng Xuebao/transactions of the Chinese Society of Agricultural Engineering. 25(12), 133-137.

Li, J.L., Sun, D.W.and Cheng, J.H. (2016d). Recent Advances in Nondestructive Analytical Techniques for Determining the Total Soluble Solids in Fruits: A Review. *Comprehensive Reviews in Food Science and Food Safety*.

Li, X., Bo, Z., Jin, L., Xiong, X.and Zhang, H. (2015). Effect of heating temperature on cell impedance properties and water distribution in apple tissue. *Nongye Gongcheng Xuebao/transactions of the Chinese Society of Agricultural Engineering*. **31**: 284-90.

Lin, H.and Ying, Y. (2009). Theory and application of near infrared spectroscopy in assessment of fruit quality: a review. *Journal of Food Measurement and Characterization*. **3**: 130-41.

Liu, D., Qu, J., Sun, D.W., Pu, H.and Zeng, X.A. (2013). Non-destructive prediction of salt contents and water activity of porcine meat slices by hyperspectral imaging in a salting process.*Innovative Food Science & Emerging Technologies*. **20**: 316-23.

Liu, R., Qi, S.and Han, D. (2015). Measurement of soluble solids content of three fruit species using universal near infrared spectroscopy models. *Journal of Near Infrared Spectroscopy*. **23**: 301-9.

Liu, Y. (2006). Study on methods of nondestructive measurement of sugar content and acidity in fruits using near-infrared spectroscopy (Ph.D Thesis). Zhejiang University. pp. 57–73.

Liu, Y.and Ying, Y. (2005). Use of FT-NIR spectrometry in non-invasive measurements of internal quality of 'Fuji' apples. *Postharvest Biology & Technology*. **37**: 65-71.

Lorente, D., Aleixos, N., Gómez-Sanchis, J., Cubero, S., García-Navarrete, O.L.and Blasco, J. (2012). Recent advances and applications of hyperspectral imaging for fruit and vegetable quality assessment. *Food and Bioprocess Technology*. **5**: 1121-42.

Louw, E.D.and Theron, K.I. (2010). Robust prediction models for quality parameters in Japanese plums (Prunus salicina L.) using NIR spectroscopy. *Postharvest Biology & Technology*. **58**: 176–84.

Lu, J., Qi, S., Liu, R., Zhou, E., Li, W., Song, S.and Han, D. (2015). Nondestructive determination of soluble solids and firmness in mix-cultivar melon using near-infrared CCD spectroscopy.*Journal of Innovative Optical Health Sciences*. **8**: 1550032.

Lu, R.and Ariana, D.P. (2011). Detection of fruit fly infestation in pickling cucumbers using a hyperspectral reflectance/transmittance imaging system ☆. *Postharvest Biology & Technology*. **81**: 44-50.

Lu, R.and Chen, Y.-R. Hyperspectral imaging for safety inspection of food and agricultural products; proceedings of the Photonics East (ISAM, VVDC, IEMB), F, 1999 [C]. International Society for Optics and Photonics.

Lu, R.and Peng, Y. (2005). Assessing peach firmness by multi-spectral scattering. *Journal of Near Infrared Spectroscopy*. **13**: 27-35.

 ACCEPTED MANUSCRIPT

Maeda, H., Ozaki, Y., Tanaka, M., Hayashi, N.and Kojima, T. (1995). Near infrared spectroscopy and chemometrics studies of temperature-dependent spectral variations of water: relationship between spectral changes and hydrogen bonds. *Journal of Near Infrared Spectroscopy*. **3**: 568-81.

Magwaza, L.S., Opara, U.L., Cronje, P.J.R., Landahl, S., Nieuwoudt, H.H., Mouazen, A.M., Nicolaï, B.M.and Terry, L.A. (2014). Assessment of rind quality of 'Nules Clementine' mandarin fruit during postharvest storage: 2. Robust Vis/NIRS PLS models for prediction of physico-chemical attributes. *Scientia Horticulturae*. **165**: 421-32.

Marguery, P.and Sangwan, B.S. (1993). Sources of variation between apple fruits within a season, and between seasons.

Mcglone, V.A., Fraser, D.G., Jordan, R.B.and Kunnemeyer, R. (2003). Internal quality assessment of mandarin fruit by vis/NIR spectroscopy. *Journal of Near Infrared Spectroscopy*. **11**: 323-32.

Merzlyak, M.N.and Chivkunova, O.B. (2000). Light-stress-induced pigment changes and evidence for anthocyanin photoprotection in apples. *Journal of Photochemistry & Photobiology B Biology*. **55**: 155-63.

Merzlyak, M.N.and Solovchenko, A.E. (2002). Photostability of pigments in ripening apple fruit: a possible photoprotective role of carotenoids during plant senescence. *Plant Science*. **163**: 881-8.

 ACCEPTED MANUSCRIPT

Merzlyak, M.N., Solovchenko, A.E.and Gitelson, A.A. (2003). Reflectance spectral features and non-destructive estimation of chlorophyll, carotenoid and anthocyanin content in apple fruit.*Postharvest Biology & Technology*. **27**: 197-211.

Munera, S., Besada, C., Jos, Eacute, Blasco, Cubero, S., Salvador, A., Talens, P.and Aleixos, N. (2017). Astringency assessment of persimmon by hyperspectral imaging. *Postharvest Biology and Technology*. 35–41.

Narendra, V.G.and Hareesh, K.S. (2010). Quality Inspection and Grading of Agricultural and Food Products by Computer Vision-a Review. *International Journal of Computer Applications*. **2**: 43-65.

Nicolaï, B., Lammerteyn, J., Veraverbeke, E.A., Hertog, M.L.a.T.M., Róth, E., Berna, A., Alamar, M.C., Verlinden, B.and Jancsók, P. (2005). Non-destructive techniques for measuring quality of fruit and vegetables. *Acta Horticulturae*. **682**: 1333-40.

Nicolai, B.M., Beullens, K., Bobelyn, E., Peirs, A., Saeys, W., Theron, K.I.and Lammertyn, J. (2007). Nondestructive measurement of fruit and vegetable quality by means of NIR spectroscopy: A review. *Postharvest biology and technology*. **46**: 99-118.

Nicolaï, B.M., Defraeye, T., Ketelaere, B.D., Herremans, E., Hertog, M.L.a.T.M., Saeys, W., Torricelli, A., Vandendriessche, T.and Verboven, P. (2014). Nondestructive Measurement of Fruit and Vegetable Quality. *Food Science and Technology*. **5**: 285-312.

 ACCEPTED MANUSCRIPT

Nordey, T., Léchaudel, M., Génard, M.and Joas, J. (2014). Spatial and temporal variations in mango colour, acidity, and sweetness in relation to temperature and ethylene gradients within the fruit. *Journal of Plant Physiology*. **171**: 1555-63.

Ornelaspaz, J.J., Yahia, E.M.and Gardeabejar, A. (2007). Identification and quantification of xanthophyll esters, carotenes, and tocopherols in the fruit of seven Mexican mango cultivars by liquid chromatography-atmospheric pressure chemical ionization-time-of-flight mass spectrometry [LC-(APcI(+))-MS]. *Journal of Agricultural & Food Chemistry*. **55**: 6628-35.

Peirs, A., Lammertyn, J., Ooms, K.and Nicolaï, B.M. (2001). Prediction of the optimal picking date of different apple cultivars by means of VIS/NIR-spectroscopy. *Postharvest Biology and Technology*. **21**: 189-99.

Peirs, A., Scheerlinck, N.and Nicolaï, B.M. (2003a). Temperature compensation for near infrared reflectance measurement of apple fruit soluble solids contents. *Postharvest Biology & Technology*. **30**: 233-48.

Peirs, A., Scheerlinck, N., Touchant, K.and Nicolai, B.M. (2002). Comparison of fourier transform and dispersive near-infrared reflectance spectroscopy for apple quality measurements. *Biosystems Engineering*. **81**: 305-11.

Peirs, A., Schenk, A.and Nicolaï, B.M. (2005). Effect of natural variability among apples on the accuracy of VIS-NIR calibration models for optimal harvest date predictions. *Postharvest Biology & Technology*. **35**: 1-13.

 ACCEPTED MANUSCRIPT

Peirs, A., Tirry, J., Verlinden, B., Darius, P.and Nicolaï, B.M. (2003b). Effect of biological variability on the robustness of NIR models for soluble solids content of apples. *Postharvest Biology & Technology*. **28**: 269-80.

Penchaiya, P.and Bobelyn, E. (2009). Non-destructive measurement of firmness and soluble solids content in bell pepper using NIR spectroscopy. *Journal of Food Engineering*. **94**: 267-73.

Peng, Y.and Lu, R. (2004). A liquid-crystal-tunable-filter-based multispectral imaging system for prediction of apple fruit firmness. *Proceedings of SPIE - The International Society for Optical Engineering*. **5587**: 91-100.

Peng, Y.and Lu, R. (2006a). Improving apple fruit firmness predictions by effective correction of multispectral scattering images. *Postharvest biology and technology*. **41**: 266-74.

Peng, Y.and Lu, R. (2006b). An LCTF-based multispectral imaging system for estimation of apple fruit firmness: Part II. Selection of optimal wavelengths and development of prediction models.*Transactions of the Asae*. **49**: 269-75.

Peng, Y.and Lu, R. (2007). Prediction of apple fruit firmness and soluble solids content using characteristics of multispectral scattering images. *Journal of Food Engineering*. **82**: 142-52.

Peng, Y.and Lu, R. (2008). Analysis of spatially resolved hyperspectral scattering images for assessing apple fruit firmness and soluble solids content ☆. *Postharvest Biology & Technology*. **48**: 52-62.

 ACCEPTED MANUSCRIPT

Pérez-Marín, D., Paz, P., Guerrero, J.E., Garrido-Varo, A.and Sánchez, M.T. (2010). Miniature handheld NIR sensor for the on-site non-destructive assessment of post-harvest quality and refrigerated storage behavior in plums. *Journal of Food Engineering*. **99**: 294-302.

Pissard, A., Baeten, V., Romnée, J.M., Dupont, P., Mouteau, A.and Lateur, M. (2012). Classical and NIR measurements of the quality and nutritional parameters of apples: a methodological study of intra-fruit variability. *Biotechnology Agronomy Society & Environment*. **16**: 294-306.

Pu, Y.Y., Feng, Y.Z.and Sun, D.W. (2015). Recent progress of hyperspectral imaging on quality and safety inspection of fruits and vegetables: a review. *Comprehensive Reviews in Food Science and Food Safety*. **14**: 176-88.

Qi, S., Oshita, S., Makino, Y.and Han, D. (2016). Influence of Sampling Component on Determination of Soluble Solids Content of Fuji Apple by Near-Infrared Spectroscopy. *Applied Spectroscopy*. 0003702816658671.

Qi, S., Song, S., Jiang, S., Chen, Y., Li, W.and Han, D. (2014). Establishment of a comprehensive indicator to nondestructively analyze watermelon quality at different ripening stages. *Journal of Innovative Optical Health Sciences*. **7**: 1350034.

Qin, J., Chao, K., Kim, M.S., Lu, R.and Burks, T.F. (2013). Hyperspectral and multispectral imaging for evaluating food safety and quality. *Journal of Food Engineering*. **118**: 157-71.

Qin, J.and Lu, R. (2007). Measurement of the absorption and scattering properties of turbid liquid foods using hyperspectral imaging. *Applied Spectroscopy*. **61**: 388-96.

ACCEPTED MANUSCRIPT

Qin, J.and Lu, R. (2008). Measurement of the optical properties of fruits and vegetables using spatially resolved hyperspectral diffuse reflectance imaging technique. *Postharvest Biology & Technology*. **49**: 355-65.

Qin, J.W.and Lu, R.F. (2009). Monte Carlo simulation for quantification of light transport features in apples. *Computers & Electronics in Agriculture*. **68**: 44-51.

Rajkumar, P., Wang, N., Eimasry, G., Raghavan, G.and Gariepy, Y. (2012). Studies on banana fruit quality and maturity stages using hyperspectral imaging. *Journal of Food Engineering*. **108**: 194-200.

Roger, J.M., Chauchard, F.and Bellon-Maurel, V. (2003). EPO–PLS external parameter orthogonalisation of PLS application to temperature-independent measurement of sugar content of intact fruits.*Chemometrics & Intelligent Laboratory Systems*. **66**: 191-204.

Sáizabajo, M., Gonzálezsáiz, J.and Pizarro, C. (2007). Temperature and path length optimisation for near infrared measurements of liquid samples: an alternative approach. *Journal of Near Infrared Spectroscopy*. **15**: 71-80.

Saure, M.C. (1990). External control of anthocyanin formation in apple. *Scientia Horticulturae*. **42**: 181-218.

Shao, Y., Zhao, C., Bao, Y.and He, Y. (2012). Quantification of Nitrogen Status in Rice by Least Squares Support Vector Machines and Reflectance Spectroscopy. *Food and Bioprocess Technology*. **5**: 100-7.

ACCEPTED MANUSCRIPT

Sheng-Zhen, Z. (2013). Effects of Setting Fruit Position on Quality of ‘Qiuhongwanmi’Peach [J]. *Southwest China Journal of Agricultural Sciences*. **3**: 066.

Smart, R.E., Smith, S.M.and Winchester, R.V. (1988). Light quality and quantity effects on fruit ripening for Cabernet Sauvignon. *American Journal of Enology & Viticulture*. **39**: 250-8.

Smillie, R.M.and Hetherington, S.E. (1999). Photoabatement by Anthocyanin Shields Photosynthetic Systems from Light Stress. *Photosynthetica*. **36**: 451-63.

Su, T.E. FERULIC ACID PRODUCTION FROM BANANA STEM WASTE: OPTIMIZATION [D]; UNIVERSITI MALAYSIA PAHANG, 2014.

Tao, Y. (1996). Spherical transform of fruit images for on–line defect extraction of mass objects. *Optical Engineering*. **35**: 344-50.

Tao y.and Wen z. (1999). An adaptive spherical image transform for high-speed fruit defect detection. *Transactions of the Asae*. **42**: 241-6.

Tee, L.H., Yang, B., Nagendra, K.P., Ramanan, R.N., Sun, J., Chan, E.S., Tey, B.T., Azlan, A., Ismail, A.and Lau, C.Y. (2014). Nutritional compositions and bioactivities of Dacryodes species: a review. *Food Chemistry*. **165**: 247-55.

Tekaya, M., Mechri, B., Cheheb, H., Attia, F., Chraief, I., Ayachi, M., Boujneh, D.and Hammami, M. (2014). Changes in the profiles of mineral elements, phenols, tocopherols and soluble carbohydrates of olive fruit following foliar nutrient fertilization. *LWT-Food Science and Technology*. **59**: 1047-53.

ACCEPTED MANUSCRIPT

Tijskens, L.M.M., Zerbini, P.E., Vanoli, M., Jacob, S., Grassi, M., Cubeddu, R., Spinelli, L.and Torricelli, A. (2006). Effects of maturity on chlorophyll-related absorption in nectarines, measured by non-destructive time-resolved reflectance spectroscopy. *International Journal of Postharvest Technology & Innovation*. **1**: 178-88.

Valente, M., Leardi, R., Self, G., Luciano, G.and Pain, J.P. (2009). Multivariate calibration of mango firmness using vis/NIR spectroscopy and acoustic impulse method. *Journal of Food Engineering*. **94**: 7-13.

Wang, H., Peng, J., Xie, C., Bao, Y.and He, Y. (2015). Fruit quality evaluation using spectroscopy technology: a review. *Sensors*. **15**: 11889-927.

Wang, N.N., Sun, D.W., Yang, Y.C., Pu, H.and Zhu, Z. (2016). Recent Advances in the Application of Hyperspectral Imaging for Evaluating Fruit Quality. *Food Analytical Methods*. 1-14.

Wedding, B.B., White, R.D., Grauf, S., Wright, C., Tilse, B., Hofman, P.and Gadek, P.A. (2011). Non-destructive prediction of 'Hass' avocado dry matter via FT-NIR spectroscopy. *Journal of the Science of Food and Agriculture*. **91**: 233-8.

Wedding, B.B., Wright, C., Grauf, S., White, R.D., Tilse, B.and Gadek, P. (2013). Effects of seasonal variability on FT-NIR prediction of dry matter content for whole Hass avocado fruit.*Postharvest Biology & Technology*. **75**: 9-16.

Wills, R., Mcglasson, B., Graham, D.and Joyce, D. (1998). Postharvest: an introduction to the physiology and handling of fruit, vegetables and ornamentals.. ed. 4.

Wülfert, F., Kok, W.T.and Smilde, A.K. (1998). Influence of temperature on vibrational spectra and consequences for the predictive ability of multivariate models. *Analytical Chemistry*. **70**: 1761-7.

Xie, L., Ye, X., Liu, D.and Ying, Y. (2011). Prediction of titratable acidity, malic acid, and citric acid in bayberry fruit by near-infrared spectroscopy. *Food Research International*. **44**: 2198-204.

Yao, Y., Chen, H., Xie, L.and Rao, X. (2013). Assessing the temperature influence on the soluble solids content of watermelon juice as measured by visible and near-infrared spectroscopy and chemometrics. *Journal of Food Engineering*. **119**: 22-7.

Zerbini, P.E., Vanoli, M., Grassi, M., Rizzolo, A., Fibiani, M., Cubeddu, R., Pifferi, A., Spinelli, L.and Torricelli, A. (2006). A model for the softening of nectarines based on sorting fruit at harvest by time-resolved reflectance spectroscopy. *Postharvest Biology & Technology*. **39**: 223-32.

Zhang, B., Huang, W., Liang, G., Li, J., Zhao, C., Liu, C.and Huang, D. (2015a). Computer vision detection of defective apples using automatic lightness correction and weighted RVM classifier.*Journal of Food Engineering*. **146**: 143-51.

Zhang, B., Huang, W., Li, J., Zhao, C., Fan, S., Wu, J., and Liu, C. (2014a). Principles, developments and applications of computer vision for external quality inspection of fruits and vegetables: A review. Food Research International. 62, 326-343.

Zhang, B., Huang, W., Li, J., Zhao, C., Liu, C., and Huang, D. (2014b). On-line identification of defect on apples using lightness correction and adaboost methods. Nongye Jixie Xuebao/transactions of the Chinese Society of Agricultural Machinery. **45(6)**: 221-226.

Zhang, B., Huang, W., Wang, C., Gong, L., Zhao, C., Liu, C.and Huang, D. (2015b). Computer vision recognition of stem and calyx in apples using near-infrared linear-array structured light and 3D reconstruction. *Biosystems Engineering*. **139**: 25-34.

Zhang, B. H., Li, J. B., Fan, S. X., Huang, W. Q., Zhang, C., and Wang, Q. Y. (2014c). Principles and applications of hyperspectral imaging technique in quality and safety inspection of fruits and vegetables. Spectroscopy and Spectral Analysis. **10(34)**, 2743-2751.

Zhang, B., Li, J., Fan, S., Huang, W., Zhao, C., Liu, C.and Huang, D. (2015c). Hyperspectral imaging combined with multivariate analysis and band math for detection of common defects on peaches (Prunus persica). *Computers & Electronics in Agriculture*. **114**: 14-24.

Zhang, B.H., Li, J.B., Zheng, L., Huang, W.Q., Fan, S.X., Zhao, C.J.and Meng, Q.D. (2015d). Development of a Hyperspectral Imaging System for the Early Detection of Apple Rottenness Caused by P enicillium. *Journal of Food Process Engineering*. **38**: 499-509.

Zhu, N., Lin, M., Nie, Y., Wu, D.and Chen, K. (2016). Study on the quantitative measurement of firmness distribution maps at the pixel level inside peach pulp. *Computers and Electronics in Agriculture*. **130**: 48-56.

Zude, M. (2003). Comparison of indices and multivariate models to non-destructively predict the fruit chlorophyll by means of visible spectrometry in apple fruit. *Analytica Chimica Acta*. **481**: 119-26.

Zude, M., Herold, B., Roger, J.M., Bellon-Maurel, V.and Landahl, S. (2006). Non-destructive tests on the prediction of apple fruit flesh firmness and soluble solids content on tree and in shelf life. *Journal of Food Engineering*. **77**: 254-60.

ACCEPTED MANUSCRIPT

Table 1- Summary of solution methods for eliminating the effects caused by geometric variability

Species	Technique	Application	Method	Geometric type	Reference
Peach	HSI	Measurement of firmness	Savitzky-Golay smoothing; Standard normal variate	shape	Zhu et al., 2016
Apple	CV	Defects segmentation	Local approach	shape	Leemans et al., 1998
Apple	CV	Defect detection	Adaptive spherical transform	shape	Tao and Wen, 1999
Citrus	HSI	Early decay detection	Mean normalization	shape	Li et al., 2016b
Apple	HSI	Firmness and SSC assessment	Mathematical equations Equation (6) and (7)	Size	Peng and Lu, 2008
Watermelon	NIR	SSC analysis	Multiplicative scatter correction	Size	Jie et al., 2013
Navel orange	CV	External defects segmentation	Edge gray value compensation algorithm	Shape	Li et al., 2009
Peach	HSI	Common defect detection	Band math	shape	Zhang et al., 2015c
Apple	HSI	Firmness and SSC prediction	Mathematical equations Equation (6) and (7)	Shape	Peng and Lu, 2007
Fruits	HSI	Measurement of the	Mathematical equations	Size	Qin and Lu, 2008

ACCEPTED MANUSCRIPT

		optical properties	Equation (6) and (7)		
Apple	HSI	Visualized prediction for sugar content	Guo's method	Shape	Guo et al., 2015
Apple	CV	Detection of defective apples	Mathematical equations Equation (4) and (5)	Shape	Zhang et al., 2015a
Orange	CV	Detection of common surface defects	Lighting transform; Low pass Butterworth filter	Shape	Li et al., 2013b
Apple	CV	Detection of surface defects	Spherical intensity transform; Equation (4) and (5)	Shape	Huang et al., 2012
Orange	CV	Correction of lighting non-uniformity	Lighting transform; B-spline lighting correction	shape	Li et al., 2014
Apple	CV	On-line identification of defects	Lighting correction method; Equation (4) and (5)	Shape	Zhang et al., 2014b
Apple	HSI	Firmness prediction	Equation (6) and (7)	Shape	Peng and Lu, 2006a
Cucumber	HSI	Detection of fruit fly infestation	Diameter correction equation	Size	Lu and Ariana, 2011
Citrus	CV	Detection of surface defects	Illumination-reflectance model	Shape	Li et al., 2011

ACCEPTED MANUSCRIPT

Apple	CV	Recognition of stem and calyx	Structured light; 3D reconstruction	Shape	Zhang et al., 2015b
Pear	HSI	Determination of SSC, pH, Firmness	Multiplicative scatter correction	Shape	Li et al., 2013a
Mushroom	HSI	Bruise damage detection	Multiplicative scatter correction; maximum normalization; median normalization and mean normalization	Shape	Gowen et al., 2008
Citrus	MSI	Identification of defects	Local thresholding method	Shape	Blasco and Moltó (2002)

Table 2- Summary of solution methods for eliminating the effects caused by biological variability

Species	Technique	Application	Method	Biological type	Reference
Apple	NIR	SSC prediction	Increasing more variability in the calibration set	Season, cultivar, origin	Peirs et al., 2003b
Apple	NIR	SSC and firmness prediction	Increasing more variability in the calibration set	Cultivar, season, shelf-life, origin	Bobelyn et al., 2010
Apple	NIR	Harvest date prediction	Average prediction of multiple fruit	Cultivar, natural variability	Peirs et al., 2005
Apricot	NIR	SSC, TA, firmness	Global models combining different varieties	Cultivar	Camps and Christen, 2009
Plum	FT-NIR	TSS,TA, sugar-to-acid ratio, firmness and weight	Multivariate prediction models	Cultivar, season	Louw and Theron, 2010
Apple	Acoustic impulse resonance frequency sensor, Vis/NIR	Firmness and SSC prediction	Fusion of the AIF and VIS data	Cultivar, shelf life	Zude, 2006

Mango	NIR	TSS and pH	Baseline correction, smoothening, MSC and second order derivatisation	Cultivar, origin	Jha et al., 2012
Apricot	ATR-FTIR	Determination of sugars and organic acids	SNV and PCA	Cultivar, maturity level	Bureau et al., 2009
Bell pepper	NIR	SSC and firmness	Increasing more variability in the calibration set, Savitzky-Golay second derivative preprocessing and EMSC	Cultivar, season	Penchaiya et al., 2009
Mandarin	Vis/NIRS	Postharvest rind physic-chemical properties prediction	Incorporating all orchards and seasons	Season, origin	Magwaza et al., 2014
Pear	Vis/NIR	Determination of SSC, pH and firmness	Smoothing and SNV processing, first-derivative	Cultivar	Li et al., 2013a
Persimmon	HSI	Astringency assessment	Increasing more maturity stage variability in the	Maturity level	Munera et al., 2017

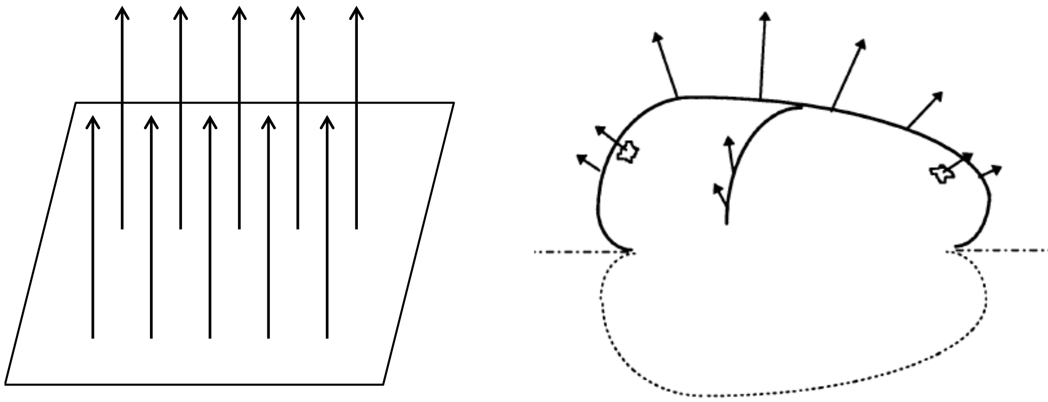
ACCEPTED MANUSCRIPT

			calibration set, SNV		
Apple	Visible spectrometry	Fruit chlorophyll prediction	First order derivative	Season, origin, maturity level	Zude, 2003
Mango	Vis/NIR spectroscopy and acoustic impulse method	Firmness prediction	Moving average smoothing, SNV, MSC, and first and second derivatives using the Savitzky Golay method	Cultivar, maturity level	Valente et al., 2009
Plum	Miniature handheld NIR sensor	Post-harvest quality and refrigerated storage behavior assessment	SNV and Detrending methods	Cultivar	Pérez-Marín et al., 2010
Apricot	FT-NIR	Quality analysis	SNV and PCA	Cultivar, maturity level	Bureau et al., 2009
Passion fruit, tomato and apricot	NIR	Prediction of internal quality traits	Smoothing, non-uniform scattering, MSC	Cultivar, maturity level	Oliveira et al., 2014
Apple	FT-NIR	Measurements of internal quality	First and second derivative	Origin	Liu et al., 2005
Mango	Vis/NIR	Internal quality index	Savitzky-Golay	Maturity level	Cortés et al.,

		prediction	smoothing, MSC		2016
Apple	NIR	Measurement of vitamin C, total polyphenol and sugar content	Increasing more variability in the calibration set	Cultivar	Pissard etal., 2012
Avocado	FT-NIR	Prediction of dry matter	Savitzy Golay spectral smoothing, SG second-derivative transformation	Intra-seasonal variation and orchard conditions	Wedding et al., 2010
Nectarines	Time-Resolved Reflectance Spectroscopy	Measuring the light absorbed	Increasing more variability in the calibration set	Maturity level	Tijskens et al., 2006
Mango	Visible spectra	Estimation indicator of external quality	Increasing more variability in the calibration set	Cultivar	Nordey et al., 2015
Tomato	NIR	Measuring the content of °Brix and carotenoids	Second derivative	Cultivar	Deák et al., 2015
Apricot	FT-NIR	Prediction of some internal quality parameters	Increasing more variability in the calibration set	Cultivar	Buyukcan et al., 2016
Apple	Vis/NIR	Nutraceutic Properties Evaluation	Second derivative	Cultivar	Beghi et al., 2012

ACCEPTED MANUSCRIPT

Mango	liquid chromatography−mass spectrometry	Identification and quantification of xanthophyll esters, carotenes, and tocopherols	Increasing more variability in the calibration set	Cultivar	Ornelas-Paz et al., 2007
Apple	NIR	Prediction of quality	Pre-processing techniques	Cultivar	Jha and Garg, 2010
Mandarin	NIR	Assessment of internal quality	First derivative, standard normal variance and detrend scatter correction	Origin, season, cultivar	Guthrie et al., 2005a,b
Apple	NIR	SSC prediction	Global model	Origin	Fan et al., 2015
Melon	NIR	Prediction of TSS	Second-derivative	Origin, season, cultivar	Guthrie et al., 2006



(a) (b)

Figure 1 Uniform reflectance of a flat platform (a) and non-uniform reflectance of an apple with curved surface (b), the length of the arrow indicates the value of reflectance on the flat and curved surface (Tao and Wen, 1999)

 ACCEPTED MANUSCRIPT

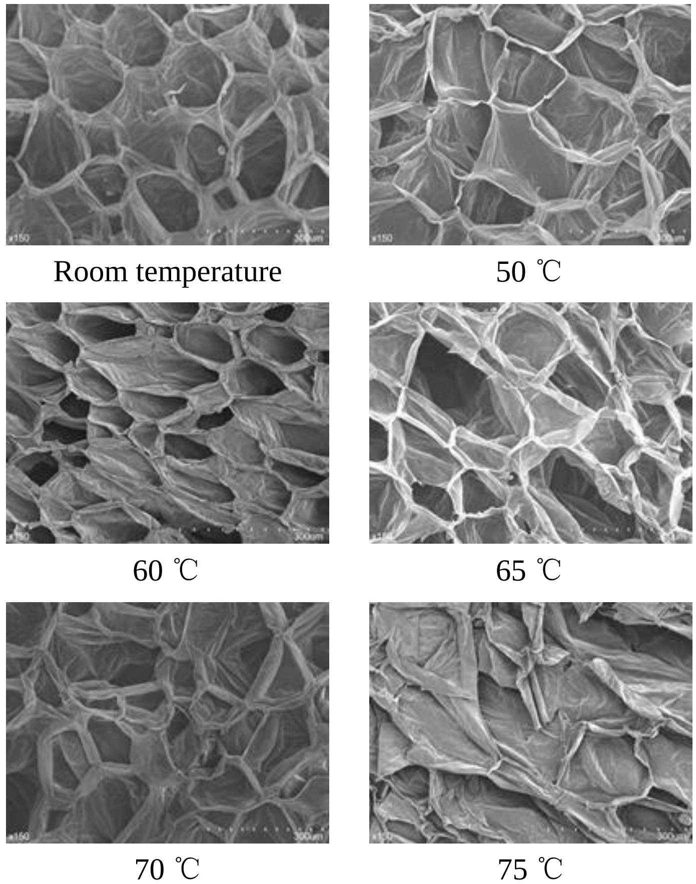


Figure 2 Microstructure of apple tissue during heating (×150 times) (Li et al., 2015)

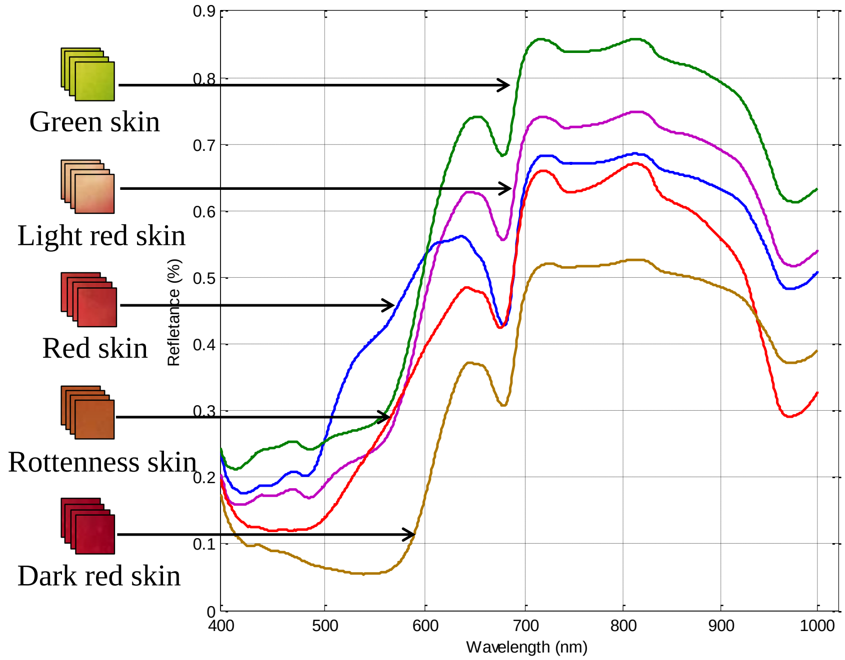


Figure 3 Representative average spectra extracted from ROIs with different color in apple hyperspectral images (Zhang et al., 2015d)

 ACCEPTED MANUSCRIPT

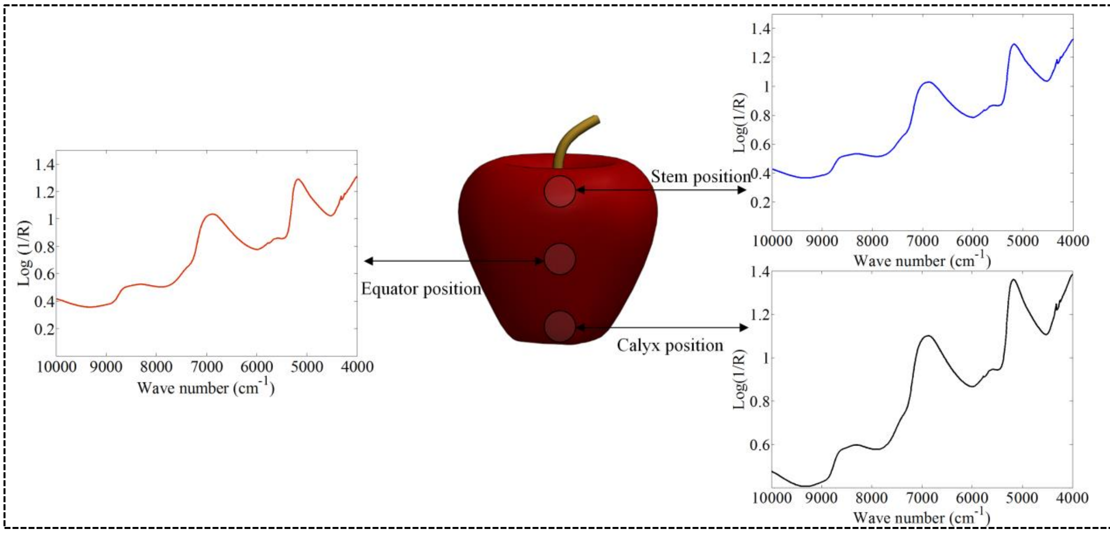


Figure 4 Three separate spectra measured around stem, equator and calyx position (Fan et al., 2016b)

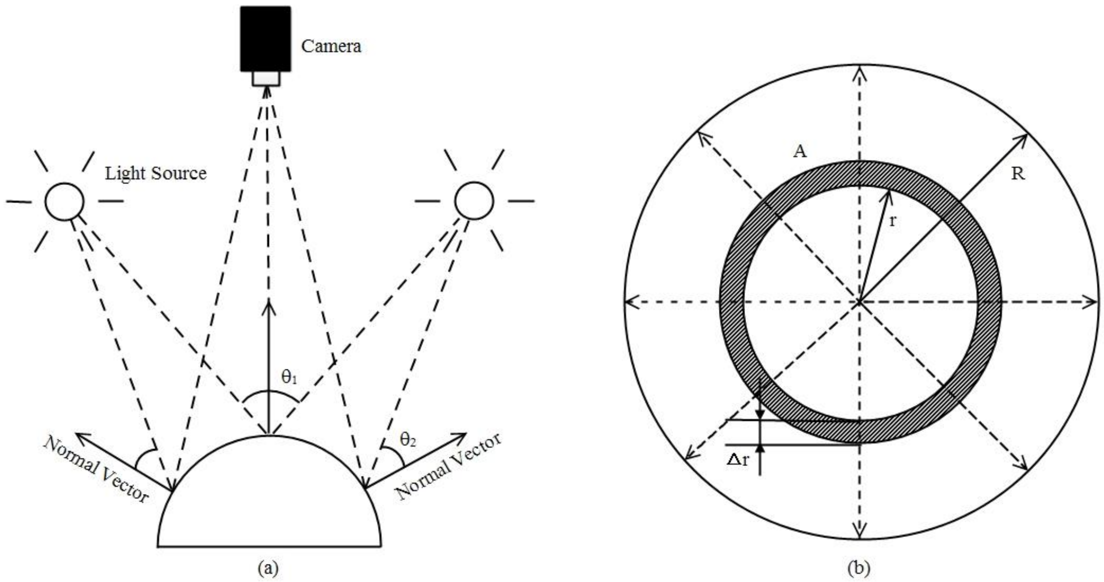


Figure 5 Diagram of the Lambertian reflection model and lightness correction method

(a) Lambertian reflection model (b) Lightness correction method (Huang et al., 2012; Zhang et al., 2015a)

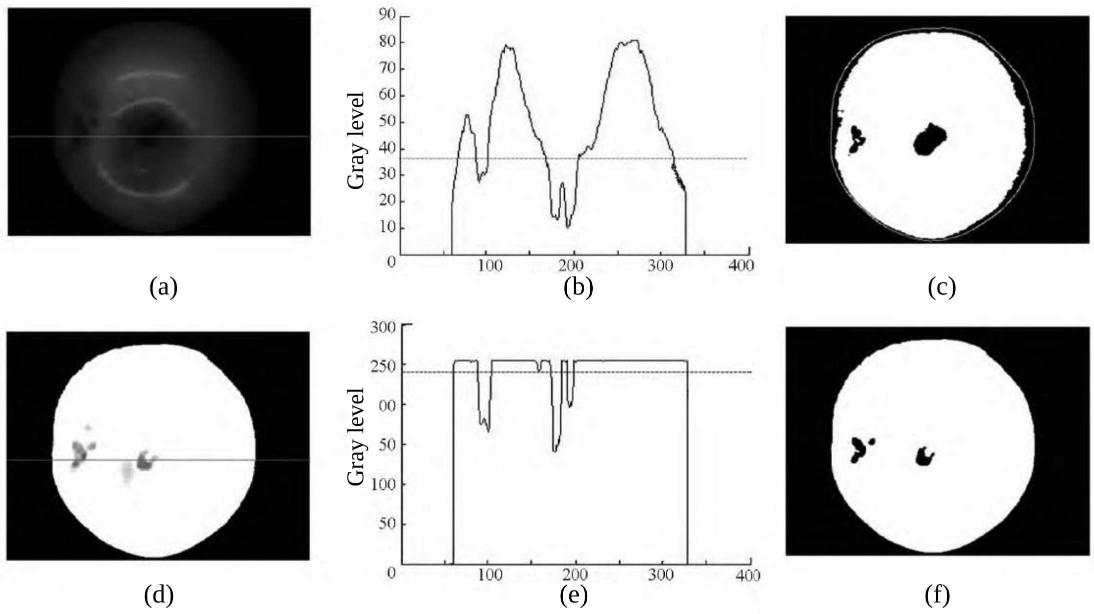


Figure 6 Results of defect candidate regions extraction before and after lightness correction

(Zhang et al., 2015d)

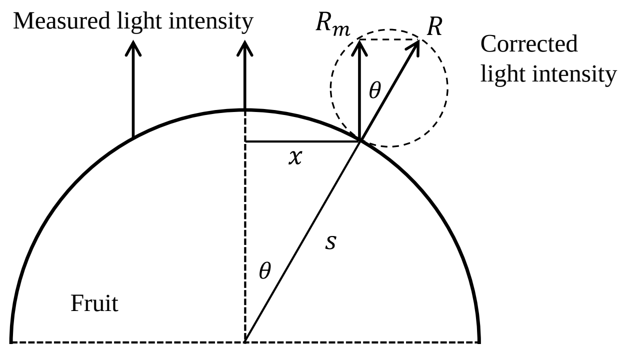
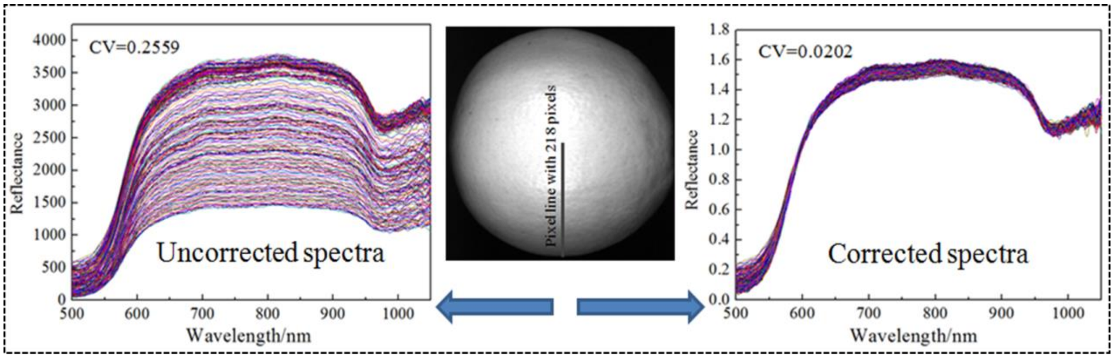
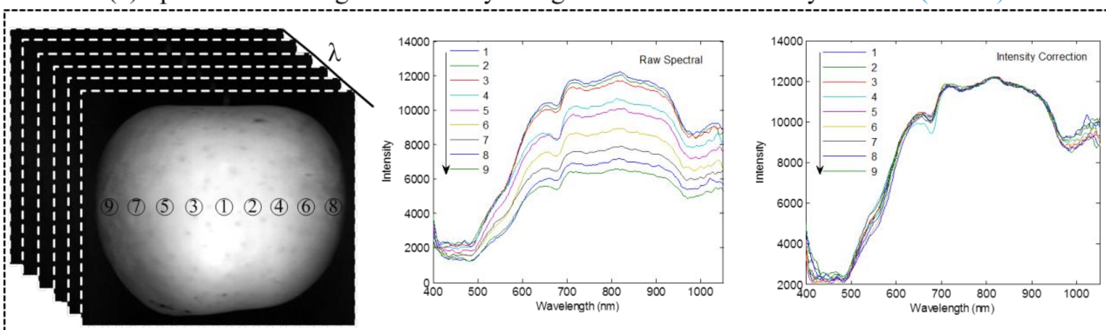


Figure 7 Correction methods for the fruit shape/size effects on the scattering distance and reflectance proposed by Peng and Lu (2007)



(a) Spectral scattering correction by using mean normalization by Li et al. (2016b)



(b) Spectral scattering correction by using Guo's method by Guo et al. (2015)

Figure 8 Correction for spectral variability caused by curved surface of fruits

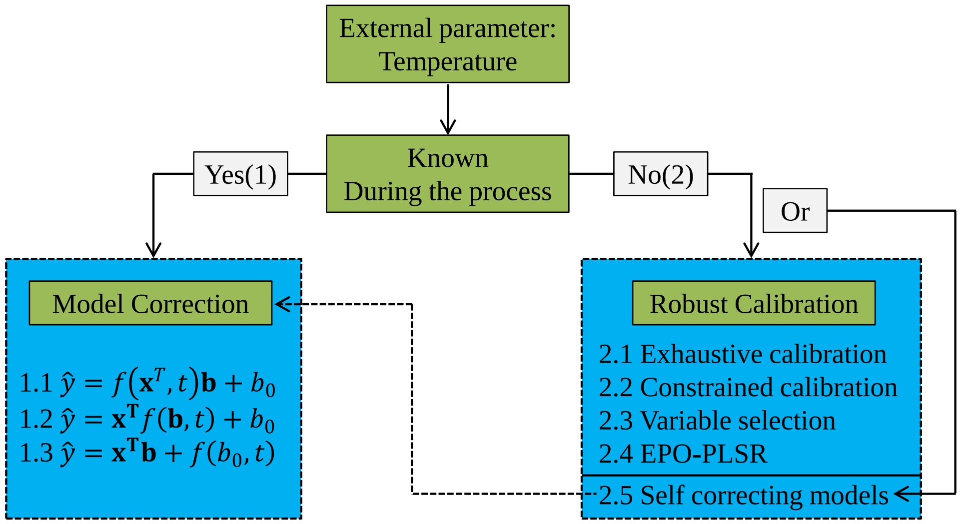


Figure 9 Methodology for correcting the external factor influence summarized by Chauchard et al. (2004)

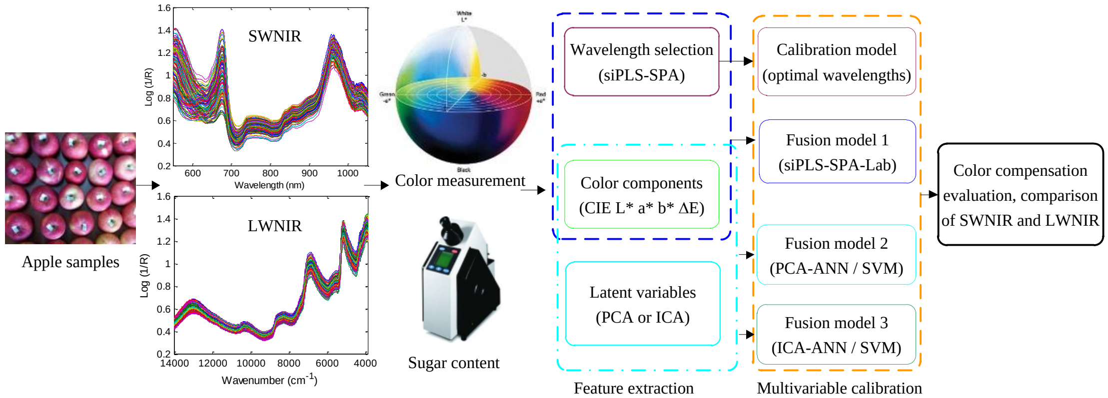


Figure 10 Schematic diagram of experimental procedure proposed by Guo et al. (2016)

