Artificial Intelligence in Agriculture 2 (2019) 85–98

Contents lists available at ScienceDirect

Artificial Intelligence in Agriculture

journal homepage: http://www.keaipublishing.com/en/journals/artificial-intelligence-in-agriculture/

Optical non-destructive techniques for small berry fruits: A review

Shuping Li [a,c], Hongpei Luo [b], Menghan Hu [a,b,*], Miao Zhang [a,d], Jianlin Feng [a], Yangtai Liu [b], Qingli Dong [b], Baolin Liu [b]

[a] Shanghai Key Laboratory of Multidimensional Information Processing, East China Normal University, Shanghai 200241, China
[b] School of Medical Instrument and Food Engineering, University of Shanghai for Science and Technology, 516 Jun Gong Rd., Shanghai 200093, China
[c] Meng Xiancheng College of ECNU, East China Normal University, Shanghai 200241, China
[d] College of Fine Arts, East China Normal University, Shanghai 200241, China

ARTICLE INFO

Article history:
Received 15 June 2019
Received in revised form 19 July 2019
Accepted 19 July 2019
Available online 29 July 2019

Keywords:
Berry fruit
Optical non-destructive measurement
Food quality and safety

ABSTRACT

Small berries including strawberry and blueberry are extensively consumed fruits with great economic values due to their characteristic flavor and appearance as well as potential health benefits. This review elaborated the optical non-destructive techniques viz. Vis-NIR spectroscopy, computer vision system, hyperspectral imaging, multispectral imaging, laser-induced method and thermal imaging, and their applications for quality and safety control of small berry fruits. The discussion regarding the photoacoustic technique, X-ray technique, Terahertz spectroscopy, odor imaging, micro-destructive testing and smart mobile terminal-based analyzer was also presented. Furthermore, we proposed our personal understanding of the technical challenges and further trends for these optical non-destructive techniques: 1) owing to the relatively low detection limit, the so-called micro-destructive techniques may be alternative to the traditional non-destructive techniques in both practical and fundamental research; 2) we suggest that the research articles like "collecting data first, and then modeling the relevant properties of agricultural products by machine learning" should be less produced in related fields. That's because such research methods are likely to be suspected of "cheating". It is recommended that some modeling competitions can be carried out in the agricultural engineering field to avoid or reduce the "cheating" model.

Contents

* Corresponding author at: Shanghai Key Laboratory of Multidimensional Information Processing, East China Normal University, Shanghai 200241, China.
E-mail address: humenghan89@163.com (M. Hu).

https://doi.org/10.1016/j.aiia.2019.07.002

1. Introduction

Small berry fruits including strawberry, blueberry, bayberry, mulberry, raspberry and gooseberry are widely consumed due to their characteristic flavor and appearance, and were proved to potentially inhibit the growth of cancer cells (Manganaris et al., 2014; Seeram et al., 2006; Zanini et al., 2015). Applying non-destructive testing techniques to the quality and safety control of small berry fruits can provide the consistent and safe as well as nutritious products for consumers (Chen et al., 2013b), thereby greatly increasing their economic values (Opara and Pathare, 2014). Optical non-destructive approaches are based on the brief principle of analyzing the signals which have been interacted with the testing materials (Mollazade et al., 2012). Over the last two decades, the optical non-destructive measurements for controlling quality and safety of food and agricultural products have attracted much scientific attention and industrial concerns (Zhang et al., 2018).

Hence, the aim of this article is to review the research progress of optical non-destructive techniques such as the Vis-NIR spectroscopy, computer vision, and hyperspectral imaging on small berry fruits. In addition, we present the personal understanding on the explanations and perspectives of optical non-destructive measurements. Table 1 summarizes optical non-detective techniques used for quality detection of small berry fruits.

2. Main optical non-destructive approaches

Table 2 demonstrates the advantages and disadvantages of optical non-destructive techniques for the detection of small berries. Detailed explanations of optical non-destructive techniques used for quality detection of small berry fruits are listed as follows.

2.1. Vis-NIR (visible-near infrared) spectroscopy

Vis-NIR spectroscopy (Vis: 380–780 nm; NIR: 780–2500 nm) has been considered as a validated screening tool for analyzing chemical and physical properties of biological materials (Balage et al., 2015; Fernandes Barbin et al., 2015). This optical spectroscopy is usually operated in (diffuse) reflectance, (diffuse) transmittance, and interactance modes, and reflectance is the mostly used mode for small berry fruits (Fig. 1). The fundamentals of Vis-NIR spectroscopy have been summarized in detail by Cozzolino et al. (2011), Magwaza et al. (2012), and Manley (2014). The reason why the Vis-NIR spectroscopy works when detecting the chemical and physical properties of biological materials such as berry fruits is: some groups in biological materials will cause absorption bands at certain spectra (Nicolai et al., 2007).

In the case of strawberry, Guo et al. (2013) established the prediction model based on NIR spectra for strawberry soluble solid content (SSC) with correlation coefficient of prediction set (Rp) of 0.939. Similar experiment was conducted by Shi et al. (2011), they attained a slightly better result in strawberry SSC prediction ($Rp = 0.941$). However, Nishizawa et al. (2009) related the NIR spectra to strawberry SSC with Rp of 0.86, and the obvious reasons for this decrease were that the sample configurations and devices as well as data processing methods were various among different researches. In this study, concentrations of glucose, fructose, and sucrose were also estimated with Rp of 0.74, 0.50 and 0.51, respectively; the low Rp value might be attributed to the lower level of these substances than SSC in strawberry. Shao and He (2008) measured the strawberry acidity using Vis-NIR reflectance spectra with Rp of 0.802. NIR qualitative application on strawberry focused on the recognition of cultivars (Kim et al., 2009; Niu et al., 2012). Relatively comprehensive NIR studies for the strawberry quality were carried out by Sanchez et al. (2012) and Giovannini et al. (2014), who used NIR data for predicting the color indicators and internal quality parameters containing SSC, firmness and titratable acidity. A research group from Turkey used NIR spectroscopy as the analytical tool for assessing the effects of ultrasound treatment (Aday et al., 2013) and active modified atmosphere packaging on strawberry (Aday and Caner, 2013; Aday et al., 2011; Kartal et al., 2012). These investigators qualitatively analyzed the reflectance or transmittance NIR profiles rather than developing the prediction models.

With regard to blueberry, Zhang et al. (2019a) leveraged the Monte Carlo multi-layered (MCML) simulation and the spectroscopy with the spectral ranges of 500–800 nm and 930–1400 nm to investigate the light propagation model of blueberries. They found that the near infrared spectral region (930–1400 nm) is sensitive to the bruise of blueberries. Their study inspires us that we can use the near infrared spectrometer to effectively detect the damage of blueberries. Sinelli et al. (2008) verified the capability of near and mid-infrared spectroscopy for evaluating both blueberry mature stage and nutritional properties including phenolic compounds, total flavonoids and total phenols contents. The performance of Vis-NIR spectroscopy was also reported to be acceptable on the quantification of blueberry total anthocyanins, total flavonoids and SSC contents as well as Young's modulus (Guidetti et al., 2009). More detailed researches were implemented by Bai et al. (2014), and they reported that the performance of NIR spectroscopy on some blueberry ingredients prediction such as organic acid was highly influenced by the measurement modes and positions. For qualitative study, Beghi et al. (2013) defined two Vis-NIR spectral ratios with linear combination as blueberry ripeness index to determine the optimal harvest date in the field. Peshlov et al. (2009) detected insect infestation in blueberries using two NIR spectroscopies and one imaging spectrograph with different wavelength ranges and detector types, and their results showed that the former two instruments outperformed the latter with accuracies of 82% and 76.9% versus 58.9%. With exception of the NIR application for monitoring the changes of chemical constituents during the dehydration treatment (Sinelli et al., 2011), very limited work has been conducted on deep-processing of blueberry.

For the other small berries, the performance of Vis-NIR spectroscopy on bayberry was evaluated for discriminating varieties (Li et al., 2007), and measuring the pH value (Li and He, 2006), titratable acidity, malic and citric acid (Xie et al., 2011). Moreover, the pH value (Shao et al., 2007) and individual sugar such as glucose, fructose and sucrose (Xie et al., 2009) in bayberry juice were quantified by the use of this spectral technique. Huang et al. (2011) reported the feasibility of Vis-NIR spectroscopy for predicting the internal quality of fruits with a bumpy surface such as mulberry.

The main disadvantage of the spectroscopic techniques is a lack of the spatial information (Manley, 2014). Although some investigators attempted to add spatial data by the use of spatially-resolved spectroscopy (Nguyen Do Trong et al., 2014a; Nguyen Do Trong et al., 2014b), it would not meet the increasing experimental demand for the non-homogenous biological materials. Unlike spectroscopic techniques, the computer vision can operate in the spatial dimension, hence allowing the detection of material external quality, especially for heterogeneous samples.

2.2. Computer vision system

Computer vision system is mainly composed of an illumination system, and a camera connecting to data processing and analysis units

Table 1
Optical non-destructive techniques for quality detection of small berry fruits.

Non-destructive technique	Food product	Used algorithm or method	Detection index	Prediction set or result	Reference
Vis-NIR spectroscopy	Strawberry	Partial least square discriminant analysis	Soluble solid content (SSC)	r_p^2=0.733, RMSEP = 0.66, RPD = 1.96	(Shen et al., 2018)
	Strawberry	Synergy interval partial least squares(siPLS) algorithms	Soluble solid content (SSC)	RMSEP = 0.2892, R_p^2=0.9390	(Guo et al., 2013)
	Strawberry	Backward interval partial least squares (BiPLS) and simulated annealing algorithm (SAA)	Soluble solid content (SSC)	R_c = 0.9478, r_p = 0.9412 RMSEC = 0.403, RMSEP = 0.428	(Shi et al., 2011)
	Strawberry	Wavelet transform (WT) combined with partial least squares PLS)	Acidity	R_c = 0.856, RMSEP = 0.026	(Shao and He, 2008)
	Blueberry	Partial least squares (PLS)	Total soluble solids (TSS), total phenols, total flavonoids and total anthocyanins, ascorbate and spectroscopic analysis	Total phenols (RMSECV = 0.14 mg catechin/g), total flavonoids (RMSECV = 0.20 mg catechin/g and RMSEP = 0.25 mg catechin/g) and total anthocyanins (RMSECV = 0.25 mg malviding/g and RMSEP = 0.22 mg catechin/g)	(Sinelli et al., 2008)
	Blueberry	Partial least squares (PLS)	Sugars, organic acids and anthocyanins	NIR spectroscopy can be used to determine the contents of constituent sugars, organic acids and anthocyanins in blueberry fruits	(Bai et al., 2014)
	Blueberry	Random frog algorithm	Hardness	R_p (R_c) = 0.9419 (0.8453), RMSEp (RMSEc) = 51.76 g (62.19 g)	(Hu et al., 2018c)
Computer vision system	Strawberry	Segmented image analysis	Changes of chromatic attributes	Only the red coordinate values of the reddish sections of the samples correlated with anthocyanin degradation	(Agudelo-Laverde et al., 2013)
	Strawberry	Ostu algorithm, HOG, H component variance	Shape and color	Average recognition rate of mature strawberries by CaffeNet = 95%	(Xin et al., 2018)
	Strawberry	Regression analysis, support vector machine (SVM), the area and perimeter parameters, Elliptic Fourier descriptor.	Weight and shape	Accuracy: for weight grading: 89.5%; for shape grading: 96.7%; average calculation time: 64 ms and 39 ms respectively	(Zhang et al., 2019b)
	Strawberry	Spectrophotometric and high performance liquid chromatography (HPLC) analyses	Levels of anthocyanins UV-excited fluorescent phenolic compounds	Anthocyanin content was well estimated based on the color values of the cut surface images, UV-excited fluorescence images were markedly correlated with the levels of those fluorescent compounds as evaluated by HPLC analysis	(Yoshioka et al., 2013)
	Strawberry	Single Shot Multibox Detector (SSD)	Geometric shape and color	Detection speed = 1.63 frames per second; average precision = 0.842	(Lamb and Mooi Choo, 2018)
	Strawberry	OmniSurface machine vision method	Volume	Weight measurement of raw produce can be used as a non-destructive method to estimate unit volume for sorting and grading purposes	(Meyer et al., 2018)
	Strawberry	Convolution neural network (CNN)	Disease	Accuracy = 92%	(Hyeon et al., 2018)
	Strawberry	3-layer neural network	Diameter, length and apex angle	The classification accuracy was between 94 and 97% and the average processing time for one strawberry (one piece) was below 0.45–0.5 s	(Oo and Aung, 2018)
	Blueberry	CIEL*a*b*scale	Quality indicators (color, presence of epicuticular wax, size, dehydratation and microbial growth)	Computer vision analysis is useful to objective quality evaluation of fruits	(Matiacevich et al., 2011)
	Blueberry	Linear SVM, KNN, TMWE and HOG.	Maturity	For KNN classifier, the best average accuracy: 86.0% for young fruit, 94.2% for intermediate fruit and 96.0% for mature fruit. The proposed TMWE classifier gives relatively high accuracy at lower computation cost	(Tan et al., 2018)
	Blueberry	Active learning algorithm, SVM	Damage	Accuracy = 0.87, precision = 0.93, recall = 0.78	(Hu et al., 2018a)
	Blueberry	ResNet, ResNeXt	Damage	Average accuracy: 0.8844 for the fine-tuned ResNet, 0.8784 for the ResNeXt; F1-score: 0.8952 for the fine-tuned ResNet, 0.8905 for the ResNeXt. Classification for each testing sample: 5.2 ms for ResNet; 6.5 ms for ResNeXt	(Wang et al., 2018)
	Blueberry	Pattern recognition algorithms, classification algorithms and cross-validation	Stem and calyx ends	The average classifier performance of 96.82 (10-fold cross-validation), the best average classifier performances of 96.7, 100.0 and 90% for shriveled blue berries, fungally decayed blueberries, and mechanically damaged blueberries	(Leiva-Valenzuela and Aguilera, 2013)
	Blueberry	One-way analysis of variance (ANOVA)	Drying rate, shrinkage, and color changes	Blueberry color can be used as an early stage indicator of quality degradation in the process of drying	(Chen and Martynenko, 2013; Vasquez et al., 2013)
	Raspberry	One-way Anova and correlation analysis, gliding box algorithm.	Color and texture	One of the results of applying this algorithm was that >80% of good products were recognized	(Markovic et al., 2018)
	Cape Gooseberry	ANN, SVMs, decision trees, KNN algorithms and principal component analysis (PCA).	Color	The models based on the L*a*b* color space and the SVM classifier achieved the highest f-measure regardless of the color spaces, and the	(Castro et al., 2019)

(continued on next page)

Table 1 (*continued*)

Non-destructive technique	Food product	Used algorithm or method	Detection index	Prediction set or result	Reference
				principal component analysis combination of color spaces improved the performance of the models at the cost of increased complexity	
	Red berry	Principal component-support vector machine (PC-SVM)	Bruises	The classification models based on fractal parameters achieved 100% total accuracy rate	(Lu et al., 2011)
	Phyllanthus emblica (gooseberry)	Colorization algorithm and extracting value parameters	Color and texture features (Minor axis, major axis, area, eccentricity)	For browning effect, they gave priority to minor axis	(Patel et al., 2013)
Hyperspectral imaging	Strawberry	Multi-band segmentation algorithm	The ratio of the bruised to unbruised areas	The improvement in performance using the decision-fusion strategy was statistically significant	(Nanyam et al., 2012)
	Strawberry	Partial least squares (PLS)	Moisture content (MC)), total soluble solids (TSS), and acidity (expressed as pH)	MC, TSS, and Ph were 0.90, 0.80, and 0.87 with SEC of 6.685, 0.233, and 0.105 and SEP of 3.874, 0.184, and 0.129	(ElMasry et al., 2007)
	Strawberry	Minimum noise fraction (MNF), successive projection algorithms (SPA), linear and non-linear algorithms	Bruise, fungal infection	Hyperspectral reflectance imaging technology has the potential for identifying defective strawberries and provides theoretical basis for the development of online classification of different defected fruits	(Liu et al., 2018)
	Strawberry	Supervised classification models	Total anthocyanin content (AC), soluble solid content (SSC) and total phenolic content (TPC)	Hyperspectral imaging technique has potential for rapid and non-invasive detection of fungal infection and for predicting and visualizing AC and SSC in strawberry fruit during storage	(Siedliska et al., 2018)
	Strawberry	Successive projection algorithm, one-way analysis of variance (ANOVA), SVM	Total water-soluble sugar (TWSS) content	Predicted TWSS content: $\boldsymbol{R_p^2}$=0.807, RPD = 2.603; excellent performance for classification accuracy among the three stages of decay: 89.4 to 95.4% for calibration; 87.0 to 94.4% for prediction	(Liu et al., 2019)
	Blueberry	Partial least squares method using cross validation	Firmness and soluble solids content (SSC)	Firmness predictions ($\boldsymbol{R}$ = 0.87), SSC predictions ($\boldsymbol{R}$ = 0.79)	(Leiva-Valenzuela et al., 2014)
	Blueberry	Regional feature selection (RFS), combined with CARS and SPA; relevance vector machines (RVM) and radial basis function (RBF).	Rot disease	The spectral information segmentation (SIS) and regional feature selection (RFS) provide a new reference method for on-line detection and sorting of blueberries	(He et al., 2019)
	Blueberry	Random frog algorithm, partial least squares (PLS)	Hardness, springiness, resilience, force, max and final force	Hardness predictions R_p (RPD) = 0.86 (1.78), springiness predictions R_p (RPD) = 0.72 (1.73), resilience predictions (RPD) = 0.79 (1.78), force max predictions (RPD) = 0.77 (1.51), final force (RPD) = 0.84 (1.72)	(Hu et al., 2015b)
	Mulberry	Principal component analysis (PCA) and partial least square regression (PLSR)	Thiophanate-methyl residue	This research confirmed the feasibility of using LIBS and HSI for the rapid detection of thiophanate-methyl residue on mulberry fruit	(Wu et al., 2019)
Multispectral imaging	Blueberry	Absorbance images applied to absorbance of pixels	Foreign materials (leaves and stems)	This research makes it possible to distinguish foreign materials from blueberry at only two wavelengths	(Sugiyama et al., 2010)
	Blueberry	Partial least squares-discriminant analysis (PLS-DA), support vector machine (SVM)	Internal bruise	Two HSI systems with complementary spectral ranges can improve blueberry internal bruising detection	(Fan et al., 2018)
Laser-induced method	Strawberry	Dynamic speckle pattern analysis	The age from observation of its dynamic speckle pattern	After only one day the ripening process of the strawberry can be detected	(Mulone et al., 2013)
	Strawberry	Partial least squares (PLS)	Native phenolic compounds	r^2 and RMSEP < 8% for *p-coumaroyl*-glucose, and r^2 = 0.99 and RMSEP < 24% for cinnamoyl-glucose	(Wulf et al., 2008)
	Blueberry	The laser air-puff	Firmness	The firmness index derived from the laser air-puff tester achieved a significant correlation with the firmness values measured by the Firmtech (R^2 = 0.8.)	(Li et al., 2011)
	Mulberry	Principal component analysis (PCA) and partial least square regression (PLSR)	Thiophanate-methyl residue	This research confirmed the feasibility of using LIBS and HSI for the rapid detection of thiophanate-methyl residue on mulberry fruit	(Wu et al., 2019)
Thermal imaging	Strawberry	Carbon isotope composition analysis	Water use efficiency (WUE)	All cultivars responded to water deficit by lowering stomatal conductance and hence increasing WUE	(Grant et al., 2012)
	Blueberry	RELIEFF algorithm	Bruise	Classification accuracy: up to 88%	(Kuzy et al., 2018)
Photoacoustic spectroscopy or	Raspberry and strawberry	Laser photoacoustic spectroscopy	Concentration of ethylene	The concentration of ethylene from nonorganic raspberry and strawberry fruits was greater than from organic ones	(Popa et al., 2014)
X-ray technique	Blueberry and blackberry	X-ray dark-field radiography	Contrast-to-noise (CNR)	In this proof-of-principle study they were able to discern between the raw and frozen state of two kinds of berries	(Nielsen et al., 2014)

(Brosnan and Sun, 2004; Zareiforoush et al., 2015). Xu and Zhao (2010) developed a computer vision system for automatically grading the strawberries in terms of shape, size and color. These appearance attributes of strawberries were utilized for the overall quality evaluations and cultivar identification (Yamamoto et al., 2015). In order to evaluate the effect of water content on freeze-dried strawberry slices,

Table 2
Summary of the advantages and disadvantages of optical non-destructive techniques for quality detection of small berries.

Main approaches	Advantages	Disadvantages
Vis-NIR spectroscopy	High spectral resolution; small amount of data; high analysis efficiency; cheap equipment.	Lack spatial resolution
Hyperspectral imaging	Having spectral and spatial resolution simultaneously.	Expensive equipment; large amount of data; low analysis efficiency.
Multispectral imaging	Having both spectral and spatial resolution; cheaper equipment than hyperspectral imaging; faster imaging speed than hyperspectral imaging.	Lower spectral resolution than hyperspectral imaging.
Laser-induced method	Low cost; quick to perform; real time evaluation.	Low spatial resolution.
Thermal imaging	Able to obtain thermal characteristic of material; having spatial information.	Strongly affected by external temperature; rather expensive equipment.
Photoacoustic spectroscopy or imaging	Strong penetrating power; go deep inside material to get deep information.	May be difficult to build equipment.
X-ray techniques	Very strong penetrating power; go deep inside material to get deep information.	Having radiation to the samples and environment
Odor imaging	Allows the differentiation among chemically diverse analyses	Poor performance of gas sensors; high power consumption

Agudelo-Laverde et al. (2013) exploited the computer vision technique to monitor the variations of color attributes. With the aid of ultraviolet light, Yoshioka et al. (2013) captured the fluorescence images of strawberries to estimate fluorescent phenolic compound levels. This indicated that the addition of light source operating outside the visible spectral range might extend the application scope of computer vision system.

Matiacevich et al. (2011) conducted the computer vision analysis for evaluating the external quality indicators of blueberries including the color, size and presence of epicuticular wax and funguses. The other group of investigators built classifiers using computer vision technique for detecting the blueberry orientations, fungal diseases and shrinkage as well as visible mechanical damages (Leiva-Valenzuela and Aguilera, 2013). The computer vision system was also configured to the dry machine for real-time measuring blueberry bulk shrinkage and color changes (Chen and Martynenko, 2013; Martynenko, 2014; Vasquez et al., 2013). It was known that the capability of computer vision technique was significantly influenced by the inconsistent ambient illumination and complex background. In order to solve these problems, Li et al. (2014) proposed a novel method based on the stepwise algorithm to identify the blueberry mature stages under natural outdoor lightings in the branch. The alternative solution for varying lighting was to use the flash light for the exposure compensation (Hu et al., 2015a; Wang et al., 2012).

With respect to the other small berries, Lu et al. (2011) successfully sorted the bayberries as the healthy and bruised categorizations using computer vision system. Patel et al. (2013) evaluated the appearance quality such as color, shape and size of gooseberry for the purpose of promoting the export industry.

Future research opportunities have been and are still being focused on multi-dimensional vision techniques (Adamczak et al., 2015). For example, Uyar and Erdogdu (2009) used 3-dimensional scanners to estimate the surface area and volume of irregular shaped fruits such as strawberry.

As shown in Fig. 2, compared to the traditional computer vision system, the on-line computer vision system is installed on the production line to achieve real-time measurement; for the multi-camera computer vision system, it can enlarge the whole view fields by putting several cameras at different angles to obtain multi-dimensional images. Fig. 3 briefly shows the main procedures and lifecycle of computer vision system.

2.3. Hyperspectral imaging

Hyperspectral imaging integrating both spectroscopic and computer vision techniques enables spectral and spatial information to be obtained simultaneously (Pu et al., 2015; Zhang et al., 2014b). Detailed information regarding to the fundamental principle of hyperspectral imaging technique could refer to a review by Wu and Sun (2013). Fig. 4 demonstrates the existing hyperspectral imaging systems used by investigators.

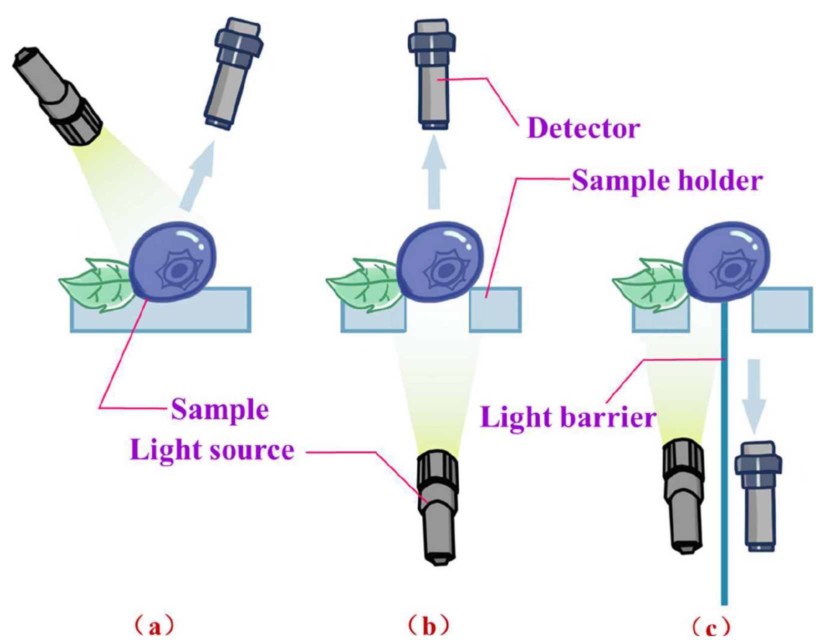

Fig. 1. Different modes for spectroscopic technique: a) reflectance mode; b) transmittance mode; c) interactance mode.

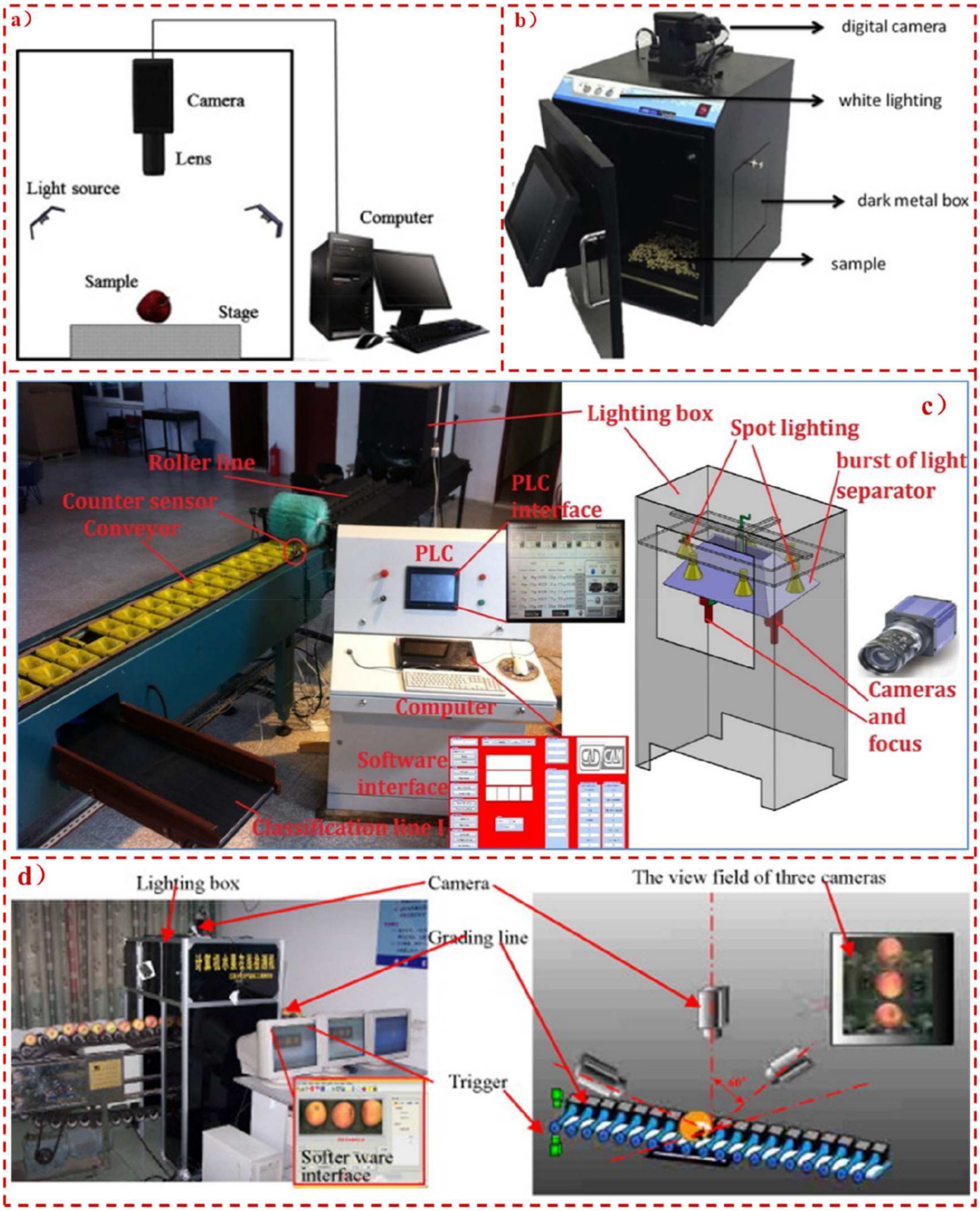

Fig. 2. Commonly used computer vision systems: a) and b) are two traditional computer vision systems by Zhang et al. (2014a) and de Oliveira et al. (2016), respectively; c) online computer vision system (Sofu et al., 2016); and d) multi-camera online computer vision system (Zou et al. Zou et al., 2010).

Nanyam et al. (2012) used hyperspectral reflectance mode to classify the bruised and unbruised areas in strawberry. Whitaker et al. (2014) reported that hyperspectral reflectance had emerged as a high throughput screening tool for strawberry nematode control. For blueberry, the firmness and soluble solids content were measured by the hyperspectral reflectance (Leiva-Valenzuela et al., 2013) and transmittance as well as their combined sensing modes (Leiva-Valenzuela et al., 2014). An improved hyperspectral imaging system was developed by Hu et al. (2015b) for predicting the comprehensive mechanical properties of blueberry derived from the compression and puncture tests using a random frog based algorithm. The scattering and interactance modes were also incorporated into this imaging system. The experimental results of Jiang et al. (2016) demonstrated that there is the significant difference between healthy and bruised tissues of blueberries at the reflectance hyperspectral range of 1280–1650 nm. Their study which used near-infrared reflectance hyperspectral imaging to screen the blueberry bruise is comprehensive and worthy of reference. Another study conducted by the same research group showed that the hyperspectral transmittance imaging technique was capability of detecting bruised blueberries as soon as 30 min after mechanical damage (Zhang et al., 2017). The feasibility of hyperspectral fluorescence imaging for small berry fruit quality and safety assessment was required in the further study (Zhang et al., 2012).

In contrast to the above literature, ElMasry et al. (2007) extracted image textural features calculated from grey-level co-occurrence matrix for classifying the strawberry ripeness stages. Recent researches in hyperspectral imaging concentrated on using spectral features such as mean spectra for the evaluation of food quality leading to the loss of spatial data. In our unpublished research work, when the textural features were acquired from the background-eliminated hypercubes (the

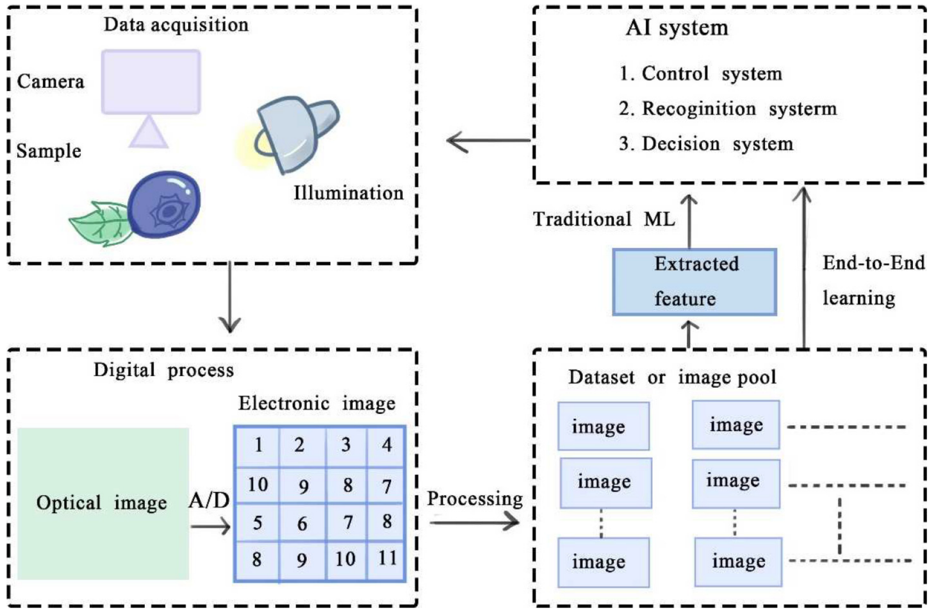

Fig. 3. Principle and lifecycle of computer vision system.

images were subjected to the image segmentation operation to eliminate the background pixels), the signal only existed on the beginning of spectral range owing to the low signal-noise ratio; however, as the background was taken into account, the signal pattern and intensity would be perfect for the following analysis (Fig. 5). Nonetheless, the texture of the background was not responsible for the fruit quality parameters; consequently, the image textural features might be not adequate for investigating food hyperspectral data, at least for blueberry.

The equipment of the polaroid in the front of lens in the hyperspectral imaging system might create the possible fundamental research opportunity. In addition, setting the suitable exposure times for the corresponding spectral intervals would make each spectrum contain more useful information (Wu and Sun, 2013). The practical applications of hyperspectral imaging were confronted by a huge amount of data, and therefore, many investigators established multispectral imaging system fitting for online detection.

2.4. Multispectral imaging

Multispectral imaging system is generally constructed on the basis of the informative wavelengths which were extracted from hundreds of contiguous spectra in hypercubes by using variable selection

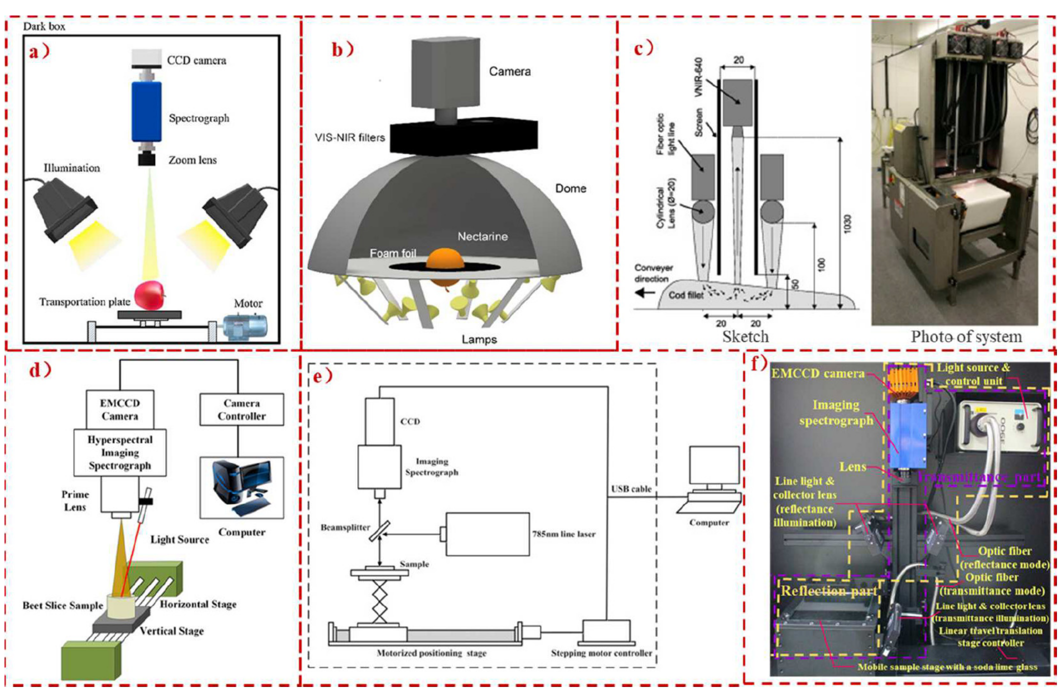

Fig. 4. Existing hyperspectral imaging systems used by investigators: a) hyperspectral reflectance imaging system (Fan et al., 2016); b) hyperspectral transmittance imaging system (Munera et al., 2019); c) hyperspectral interactance imaging system (Sivertsen et al., 2012); d) hyperspectral scattering imaging system (Pan et al., 2016); e) hyperspectral Raman imaging system (Wang et al., 2017a; Wang et al., 2017b; Wang et al., 2017c); f) the pushbroom hyperspectral reflectance, transmittance and interactance imaging system modified from (Hu et al., 2016).

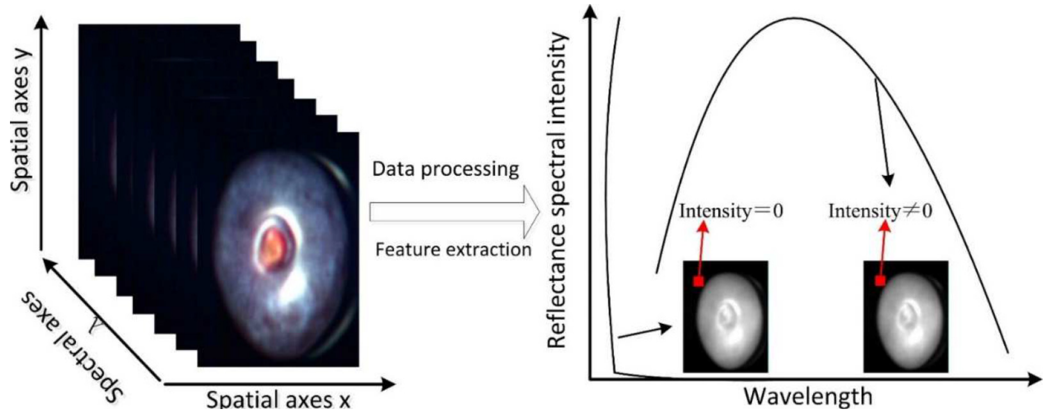

Fig. 5. Typical image textural signals for blueberry original and background-eliminated hypercubes.

algorithms. Fig. 6 shows a multispectral computer vision system, including camera, multi-spectral device, filters, lens and halogen lamp. Liu et al. (2014) concluded that the multispectral imaging coupled with appropriate calibration models could rapidly and non-destructively determine the strawberry quality traits and maturity stages. Yang et al. (2012) used multispectral sensing to preliminarily distinguish blueberry fruit in various ripeness stages and leaves for estimating its yield in the field. The detection of foreign substances in blueberries was carried out by the use of the spectral imaging at the wavelengths of 1268 nm and 1317 nm (Sugiyama et al., 2010).

2.5. Laser-induced method

According to the previous literature, the later-induced biospeckle technology could be categorized into the static and dynamic biospeckle. The former, also termed as backscattering imaging, has been extensively used for food quality evaluation as the simple imaging processing techniques were required in its data analysis (De Belie et al., 1999; Hashim et al., 2013). The advantage compared to the static biospeckle is that, due to the additional temporal dimension, the dynamic biospeckle can reflect the particle movement at the cellular and/or sub-cellular scale (Zdunek and Herppich, 2012). However, the requirement of video

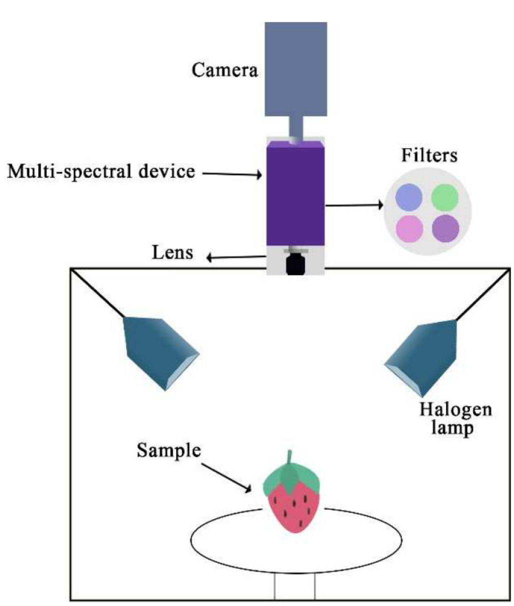

Fig. 6. Multispectral imaging system.

processing techniques hindered the applications of dynamic biospeckle on on-line quality detection. For strawberries, Mulone et al. (2013) determined their maturation via analyzing the statistical descriptors of dynamic biospeckle. In our preliminary experiments (Hu et al., 2013), we found that the biospeckle quality captured by zoom lens was superior to that by fixed lens (Fig. 7). As shown in Fig. 7, the four haloes could be clearly observed on the zoom lens biospeckle image, indicating the much more useful information. Therefore, it was necessary to compare the effects of fixed and zoom lens biospeckles on the final experimental results.

In terms of other laser-excited techniques, Wulf et al. (2008) tested the potential usage of the laser-induced fluorescence spectroscopy for quantifying the blueberry *p*-coumaroyl-glucose and cinnamoyl-glucose contents. Li et al. (2011) estimated the blueberry firmness using a laser air-puff instrument with the correlation coefficient of 0.80 related to the traditional destructive method.

Raman spectroscopy could be considered as a laser-induced technique for the reason that the Raman signals were excited by the laser. In most cases, Raman spectroscopy was operated in destructive ways (Fan et al., 2014). Some researchers used Raman spectroscopy as the non-destructive (Dhakal et al., 2014; He et al., 2014; Qin et al., 2012) and micro-destructive (Fang et al., 2015) analytical tools for controlling food safety and quality. The discussion of micro-destructive techniques would be presented in Section 3.6. To date, there is still no relevant study for the use of Raman spectroscopy on small berry fruits.

3. Other optical non-destructive approaches

3.1. Thermal imaging

Thermal imaging is a passive and energy efficient green imaging technique, and it can capture the emitted energy from the objects whose absolute temperature is higher than zero without any external stimulation such as harmful radiation and illumination (Hu et al., 2018b). Depending on the users' requirements, the infrared ranges are very different. Generally, we consider that the object emits the thermal radiation within the spectral range from 3 μm to 13 μm (Lu and Lu, 2017). Thermal imaging is initially applied to military (Gowen et al., 2010; Opara and Pathare, 2014), and then used in biomedical engineering (Hu et al., 2017) and criminal investigation (Li et al., 2018). Recently, it has also been used as a non-destructive technique for various agricultural applications, such as the detections of insect infestation (Mahajan et al., 2015), foreign substances (Vadivambal and Jayas, 2011) and bruise damage (Baranowski et al., 2012). Meinlschmidt and Margner (2002) verified the feasibility of using the thermal imaging to distinguish the foreign bodies among the small berry fruits. The principle of using thermal imaging to distinguish the foreign bodies among the

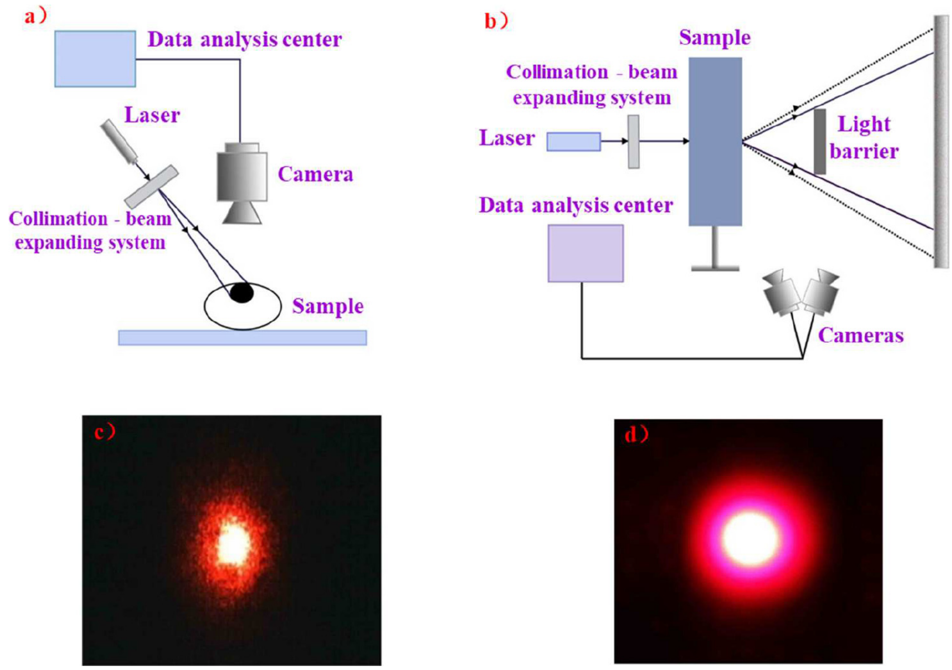

Fig. 7. Reflectance-type (a) and transmission-type (b) biospeckle measurement devices; (c) and (d) are biospeckle images obtained by fixed lens and zoom lens, respectively.

small berry fruits is that: any plant breathes and exhales heat; the berry fruit is one of plants, and therefore it breathes more intense than other foreign objects; we can use the difference of thermal properties to effectively screen foreign body out. The capability of thermal imaging for early detecting the physical, chemical or biological damages of small berry fruits should be explored in the further study.

3.2. Photoacoustic spectroscopy or imaging

Based on photoacoustic effect, the photoacoustic measurement is a unique technique monitoring the non-radiative relaxation processes (Bageshwar et al., 2010). In other words, this technique uses the modulated or pulsed laser source to excite the local heating of the sample matrix, thus allowing the subsequent acquisition of resulting signal in the sound form (Bageshwar et al., 2010). The basic components of photoacoustic technique include the excitation source, acoustic cells, and acoustic detector (West et al., 1983). Due to the ability of detecting acoustic or ultrasonic signals from optically thick samples, the photoacoustic approach has been considered as “super vision” to offer an alternative or a complementary strategy to pure optical technologies (Meralitimes, 2015).

Recently, in food and agricultural research, the photoacoustic approach has been used for determining nitrogen in rapeseed (Lu et al., 2015) and quantifying pesticide residue in apple cuticle (Liu et al., 2015). In terms of small berries, Popa et al. (2014) validated the hypothesis that the nonorganic raspberry and strawberry fruits released more ethylene gas than organic ones via the photoacoustic spectroscopy. Since most of biological materials are turbid or opaque in nature, the photoacoustic spectroscopy or the imaging technique deserves a lot of attention in the further study.

3.3. X-ray technique

X-ray technique is commonly applied to security inspection in airports and customs, and recently it has been extensively used in food and agricultural domain (Jiang et al., 2008; Mathanker et al., 2013a), including detecting fruit pest infestation (Chuang et al., 2011), determining food density (Kelkar et al., 2015), inspecting the foreign bodies (Li et al., 2015), charactering fruit internal structure (Magwaza and

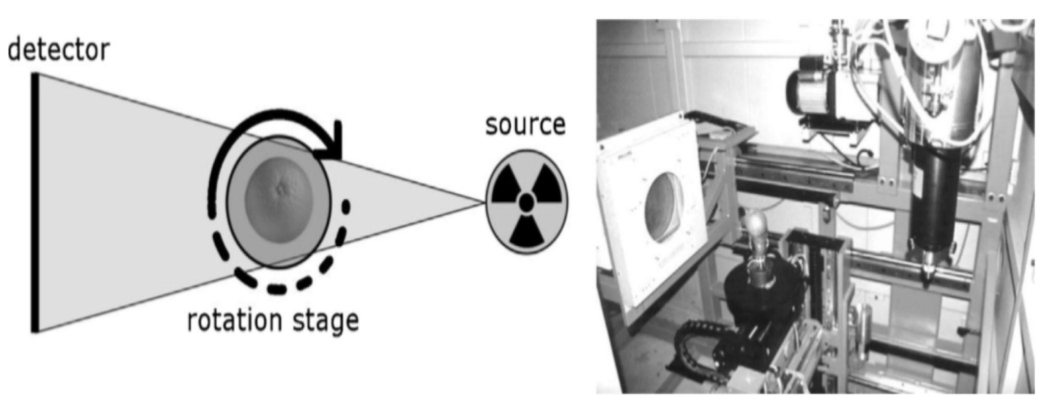

Fig. 8. A schematic presentation of X-ray technique for fruits detection (van Dael et al., 2016).

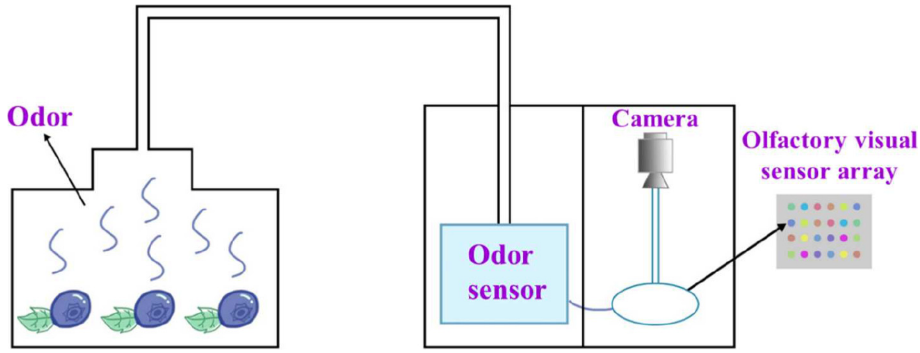

Fig. 9. A schematic of odor visualization.

Opara, 2014) and micro-structure (Cantre et al., 2014). The fundamental principle behind X-ray techniques inclusive of X-ray Computed Tomography (CT) is based on the fact that the radial absorption capabilities are different between the foreign materials and food produces (Nielsen et al., 2013). Fig. 8 shows a schematic presentation of the X-ray computed tomography geometry (left) and the actual setup (right).

For small berry fruits, Nielsen et al. (2014) differentiated frozen and defrosted blueberry and blackberry fruits from the X-ray images. In the further research, large data volumes in X-ray CT posed a challenge in image acquisition and processing. Developments in the multimodal machine vision system containing computer vision, hyperspectral imaging and X-ray technique (Wang and Li, 2015) bring not only more useful information, but also the increasing redundant information.

3.4. Terahertz (THz) technology

In contrast to X-ray systems, THz systems can offer not only the discrimination of low-density organic materials such as insects and plastics in a food matrix but also the safe detection owing to the non-ionizing radiation (Gyeongsik et al., 2014; Ok et al., 2015). In food and agricultural area, due to the sensitivity to active substances, the strong penetration into specific materials, the relatively low photon energy and the high resolution (Won-Hui and Wangjoo, 2014), THz technology has received considerable attention for the detection of chemical and physical contaminants in food (Gyeongsik et al., 2014; Qin et al., 2015), the identification of transgenic food (Liu and Li, 2014; Xu et al., 2015) and the application in fundamental research (Shiraga et al., 2013). The detailed fundamentals and applications of THz technology could be found in the reviews by El Haddad et al. (2013), Gowen et al. (2012), Mathanker et al. (2013b), and Qin et al. (2013).

According to our unpublished data, the THz reflectance spectroscopy was validated to be not applicable for blueberry quality evaluation because of the curved surface (data not shown). Further researches are required to overcome some technical hurdles such as the attenuation by water and scattering by inhomogeneous media (Ok et al., 2014).

3.5. Odor visualization

Odor visualization/imaging is based on colorimetric sensor array to produce the unique color fingerprints using image acquisition devices such as the scanner (Chen et al., 2013a) and camera (Chen et al., 2013b), which in turn allows the differentiation among chemically diverse analytes (Rakow and Suslick, 2000). As Fig. 9 displays, the odor produced by fruits is absorbed by odor sensor, generating signals which will be processed by olfactoty visual sensor array then, and the processed signals will change into a kind of specific spectrum. Finally, the device such as camera will capture the spectral images. Some investigators have extensively applied this techniques to food and agricultural area (Chen et al., 2013b). The further research on small berries can be explored due to the volatile materials emitted by these fruits during the postharvest operations.

3.6. Micro-destructive testing

Due to the intrinsic limitations in non-destructive measurements such as the low detection limit, we presented a novel concept termed as a micro-destructive method in food and agricultural area.

Such micro-destructive technique must allow the minimally invasive assessment of food and agricultural products – the samples after testing should maintain the basically same quality compared to those before testing. In addition, the biological behavior of the slightly destructive samples should be the same as completely healthy samples. This technique has been used for the diagnostic study on dyes (Aceto et al., 2015) and archaeometric investigation of Roman tesserae (van der Werf et al., 2009). One of the possible optical micro-destructive frameworks which can be applicable for fruits is proposed in Fig. 10. Changing the types of the generator and detectors as shown in Fig. 10 enables the other measurement modes like the electrical micro-destructive testing.

3.7. Smart mobile terminal-based analyzer

Smart mobile terminals equipped with various sensors such as the excited illumination source and accelerometer make them promising tools for the diverse practical applications (Hossain et al., 2015a; Pongnumkul et al., 2015; Preechaburana et al., 2014), including the color evaluation (Intaravanne and Sumriddetchkajorn, 2015;

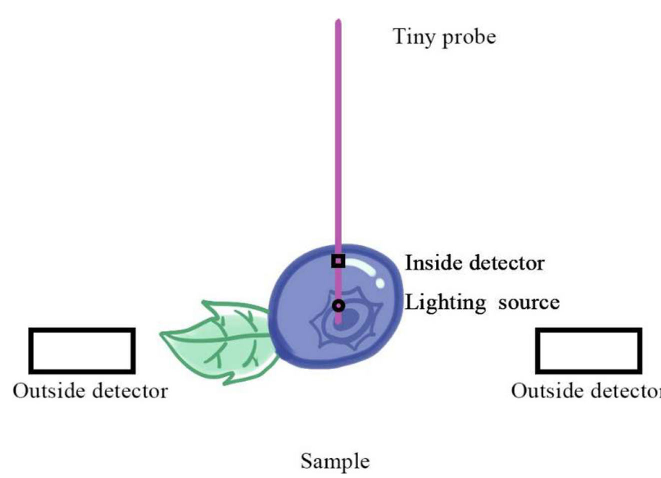

Fig. 10. Schematic diagram of a possible optical micro-destructive system.

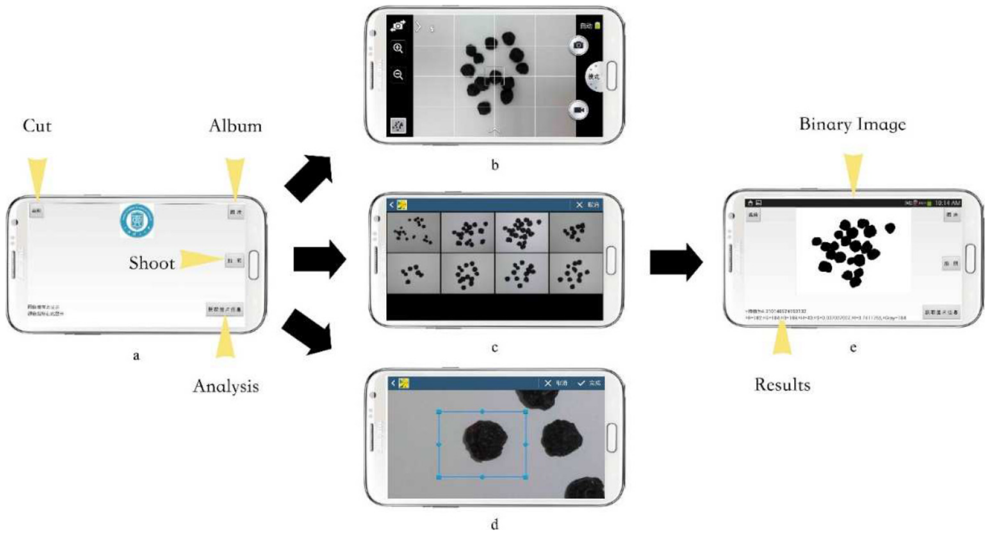

Fig. 11. Procedures of the Android app developed for color and image textural analysis of dried blueberries: a) main interface; b) shoot interface; c) album interface; d) cutting interface; e) results interface.

Intaravanne et al., 2012; Sumriddetchkajorn et al., 2014), chemical component determination (Hossain et al., 2015b; Lopez-Ruiz et al., 2014; Masawat et al., 2015) and dietary assessment (Oliveira et al., 2014). Pertot et al. (2012) established a visual identificator based on the smart terminals including the mobile phone for assisting non-professional persons to distinguish strawberry diseases. We have also developed an Android app capable of color and image textural analysis (Fig. 11), and the following work is to apply this app for analyzing the appearance quality of small berry fruits or the other biological materials.

4. Conclusion

This review summarized the optical non-destructive techniques and their applications for quality and safety control of small berry fruits. Also, we presented our personal understanding of the technical challenges and further trends for these optical non-destructive techniques. Particularly, due to the relatively low detection limit, we believe that the so-called micro-destructive techniques may be alternative to the traditional non-destructive techniques in both practical and fundamental research. In addition, we suggest that the research articles like "collecting data first, and then modeling the relevant properties of agricultural products by machine learning" should be less produced in related fields. That's because such research methods are likely to be suspected of "cheating": the researchers of a paper can constantly adjust the parameters of models in the validation dataset to make the model acceptable before submitting the article. As the data is in hands of the researchers, they are always capable to figure out an appropriate model through various methods. However, from a practical perspective, such models may not be very significant. Hence, it is recommended that some modeling competitions as said below can be carried out in the agricultural engineering field. In the match, the organizer keeps part of the testing data and opens the training data and the validation data to the public so that the participants have access to them to do the modeling research. After the match, competitors hand in models for verification by the organizer, while the models with better performance can be published in relevant conferences or journals. This measure is of great significance as it will help the academia and even the industry find out excellent models while preventing the "cheating" models appearing.

Acknowledgements

This work was supported by the Shanghai Sailing Program under Grant 19YF1414100, the China Postdoctoral Science Foundation funded project under Grant 2016M600315, the Innovation Fund Project for Graduate Student of Shanghai (JWCXSL1401), and the STCSM (No. 18DZ2270700). We are grateful to Prof. Yi-Ming Zhu, Dr. Hong-Wei Zhao, Mr. Wei Xiao and Mr. Jing Chen from School of Optical-Electrical and Computer Engineering, University of Shanghai for Science and Technology for their valuable helps in THz experiments. We are also grateful to Dr. Chao-Hui Feng from College of Food Science, Sichuan Agricultural University.

References

Zou, X.-b., Zhao, J.-w., Li, Y., Holmes, M., 2010. In-line detection of apple defects using three color cameras system. Comput. Electron. Agric. 70, 129–134.
Niu, X.-y., Shao, L.-m., Zhao, Z.-l., Zhang, X.-y., 2012. Nondestructive discrimination of strawberry varieties by NIR and BP-ANN. Spectrosc. Spectr. Anal. 32, 2095–2099.
Aceto, M., Arrais, A., Marsano, F., Agostino, A., Fenoglio, G., Idone, A., Gulmini, M., 2015. A diagnostic study on folium and orchil dyes with non-invasive and micro-destructive methods. Spectrochim. Acta A Mol. Biomol. Spectrosc. 142, 159–168.
Adamczak, L., Chmiel, M., Florowski, T., Pietrzak, D., Witkowski, M., Barczak, T., 2015. A potential use of 3-D scanning to evaluate the chemical composition of pork meat. J. Food Sci. 80, E1506–E1511.
Aday, M.S., Caner, C., 2013. The shelf life extension of fresh strawberries using an oxygen absorber in the biobased package. LWT-Food Science and Technology 52, 102–109.
Aday, M.S., Caner, C., Rahvali, F., 2011. Effect of oxygen and carbon dioxide absorbers on strawberry quality. Postharvest Biol. Technol. 62, 179–187.
Aday, M.S., Temizkan, R., Buyukcan, M.B., Caner, C., 2013. An innovative technique for extending shelf life of strawberry: ultrasound. Lwt-Food Science and Technology 52, 93–101.
Agudelo-Laverde, L.M., Schebor, C., Buera, M.D., 2013. Water content effect on the chromatic attributes of dehydrated strawberries during storage, as evaluated by image analysis. Lwt-Food Science and Technology 52, 157–162.
Bageshwar, D.V., Pawar, A.S., Khanvilkar, V.V., Kadam, V.J., 2010. Photoacoustic spectroscopy and its applications–a tutorial review. Eurasian J. Anal. Chem. 5, 187–203.
Bai, W.M., Yoshimura, N., Takayanagi, M., 2014. Quantitative analysis of ingredients of blueberry fruits by near infrared spectroscopy. J. Near Infrared Spectrosc. 22, 357–365.
Balage, J.M., Silva, S.D.E., Gomide, C.A., Bonin, M.D., Figueira, A.C., 2015. Predicting pork quality using Vis/NIR spectroscopy. Meat Sci. 108, 37–43.
Baranowski, P., Mazurek, W., Wozniak, J., Majewska, U., 2012. Detection of early bruises in apples using hyperspectral data and thermal imaging. J. Food Eng. 110, 345–355.
Beghi, R., Giovenzana, V., Spinardi, A., Guidetti, R., Bodria, L., Oberti, R., 2013. Derivation of a blueberry ripeness index with a view to a low-cost, handheld optical sensing device for supporting harvest decisions. Trans. ASABE 56, 1551–1559.
Brosnan, T., Sun, D.W., 2004. Improving quality inspection of food products by computer vision - a review. J. Food Eng. 61, 3–16.
Cantre, D., East, A., Verboven, P., Trejo Araya, X., Herremans, E., Nicolaï, B.M., Pranamornkith, T., Loh, M., Mowat, A., Heyes, J., 2014. Microstructural characterisation of commercial kiwifruit cultivars using X-ray micro computed tomography. Postharvest Biol. Technol. 92, 79–86.
Castro, W., Oblitas, J., De-la-Torre, M., Cotrina, C., Bazan, K., Avila-George, H., 2019. Classification of cape gooseberry fruit according to its level of ripeness using machine learning techniques and different color spaces. IEEE Access 7, 27389–27400.

Chen, Y.G., Martynenko, A., 2013. Computer vision for real-time measurements of shrinkage and color changes in blueberry convective drying. Dry Technology 31, 1114–1123.

Chen, Q., Liu, A., Zhao, J., Ouyang, Q., 2013a. Classification of tea category using a portable electronic nose based on an odor imaging sensor array. J. Pharm. Biomed. Anal. 84, 77–89.

Chen, Q.S., Zhang, C.J., Zhao, J.W., Ouyang, Q., 2013b. Recent advances in emerging imaging techniques for non-destructive detection of food quality and safety. TrAC Trends Anal. Chem. 52, 261–274.

Chuang, C.-L., Ouyang, C.-S., Lin, T.-T., Yang, M.-M., Yang, E.-C., Huang, T.-W., Kuei, C.-F., Luke, A., Jiang, J.-A., 2011. Automatic X-ray quarantine scanner and pest infestation detector for agricultural products. Comput. Electron. Agric. 77, 41–59.

Cozzolino, D., Cynkar, W.U., Shah, N., Smith, P., 2011. Multivariate data analysis applied to spectroscopy: potential application to juice and fruit quality. Food Res. Int. 44, 1888–1896.

van Dael, M., Lebotsa, S., Herremans, E., Verboven, P., Sijbers, J., Opara, U.L., Cronje, P.J., Nicolai, B.M., 2016. A segmentation and classification algorithm for online detection of internal disorders in citrus using X-ray radiographs. Postharvest Biol. Technol. 112, 205–214.

De Belie, N., Tu, K., Jancsók, P., De Baerdemaeker, J., 1999. Preliminary study on the influence of turgor pressure on body reflectance of red laser light as a ripeness indicator for apples. Postharvest Biol. Technol. 16, 279–284.

Dhakal, S., Li, Y.Y., Peng, Y.K., Chao, K.L., Qin, J.W., Guo, L.H., 2014. Prototype instrument development for non-destructive detection of pesticide residue in apple surface using Raman technology. J. Food Eng. 123, 94–103.

El Haddad, J., Bousquet, B., Canioni, L., Mounaix, P., 2013. Review in terahertz spectral analysis. TrAC Trends Anal. Chem. 44, 98–105.

ElMasry, G., Wang, N., ElSayed, A., Ngadi, M., 2007. Hyperspectral imaging for nondestructive determination of some quality attributes for strawberry. J. Food Eng. 81, 98–107.

Fan, Y., Lai, K., Rasco, B.A., Huang, Y., 2014. Analyses of phosmet residues in apples with surface-enhanced Raman spectroscopy. Food Control 37, 153–157.

Fan, S., Zhang, B., Li, J., Liu, C., Huang, W., Tian, X., 2016. Prediction of soluble solids content of apple using the combination of spectra and textural features of hyperspectral reflectance imaging data. Postharvest Biol. Technol. 121, 51–61.

Fan, S.X., Li, C.Y., Huang, W.Q., Chen, L.P., 2018. Data fusion of two hyperspectral imaging systems with complementary spectral sensing ranges for blueberry bruising detection. Sensors 18, 4463.

Fang, H., Zhang, X., Zhang, S.J., Liu, L., Zhao, Y.M., Xu, H.J., 2015. Ultrasensitive and quantitative detection of paraquat on fruits skins via surface-enhanced Raman spectroscopy. Sensors Actuators B Chem. 213, 452–456.

Fernandes Barbin, D., Valous, N.A., Passos Dias, A., Camisa, J., Hirooka, E.Y., Yamashita, F., 2015. VIS-NIR spectroscopy as a process analytical technology for compositional characterization of film biopolymers and correlation with their mechanical properties. Materials Science and Engineering: C, Materials for Biological Applications 56, 274–279.

Giovannini, D., Quacquarelli, I., Ranieri, M., Faedi, W., 2014. Feasibility study of NIR application to strawberry internal fruit quality traits. VII International Strawberry Symposium 1049, 947–954.

Gowen, A.A., Tiwari, B.K., Cullen, P.J., McDonnell, K., O'Donnell, C.P., 2010. Applications of thermal imaging in food quality and safety assessment. Trends Food Sci. Technol. 21, 190–200.

Gowen, A.A., O'Sullivan, C., O'Donnell, C.P., 2012. Terahertz time domain spectroscopy and imaging: emerging techniques for food process monitoring and quality control. Trends Food Sci. Technol. 25, 40–46.

Grant, O.M., Davies, M.J., James, C.M., Johnson, A.W., Leinonen, I., Simpson, D.W., 2012. Thermal imaging and carbon isotope composition indicate variation amongst strawberry (Fragaria × ananassa) cultivars in stomatal conductance and water use efficiency. Environ. Exp. Bot. 76, 7–15.

Guidetti, R., Beghi, R., Bodria, L., Spinardi, A., Mignani, I., Folini, L., 2009. Prediction of blueberry (Vaccinium corymbosum) ripeness by a portable Vis-NIR device. IX International Vaccinium Symposium 810, 877–885.

Guo, Z., Huang, W., Chen, L., Wang, X., Peng, Y., 2013. Nondestructive evaluation of soluble solid content in strawberry by near infrared spectroscopy. Proc. SPIE Int. Soc. Opt. Eng. 8761, 87610O.

Gyeongsik, O., Hyun Jung, K., Hyang Sook, C., Sung-Wook, C., 2014. Foreign-body detection in dry food using continuous sub-terahertz wave imaging. Food Control 42, 284–289.

Hashim, N., Pflanz, M., Regen, C., Janius, R.B., Abdul Rahman, R., Osman, A., Shitan, M., Zude, M., 2013. An approach for monitoring the chilling injury appearance in bananas by means of backscattering imaging. J. Food Eng. 116, 28–36.

He, L., Chen, T., Labuza, T.P., 2014. Recovery and quantitative detection of thiabendazole on apples using a surface swab capture method followed by surface-enhanced Raman spectroscopy. Food Chem. 148, 42–46.

He, K., Tian, Y., Qiao, S., Yao, P., Gu, W., 2019. Detection of rot blueberry disease by hyperspectral imaging with SIS and RFS. Chinese Journal of Luminescence 40, 413–421.

Hossain, M.A., Canning, J., Ast, S., Cook, K., Rutledge, P.J., Jamalipour, A., 2015a. Combined "dual" absorption and fluorescence smartphone spectrometers. Opt. Lett. 40, 1737–1740.

Hossain, M.A., Canning, J., Ast, S., Rutledge, P.J., Yen, T.L., Jamalipour, A., 2015b. Lab-in-a-phone: smartphone-based portable fluorometer for pH measurements of environmental water. IEEE Sensors J. 15, 5095–5102.

Hu, M., Dong, Q., Liu, B., Tu, K., Song, X., 2013. Application of biospeckle on analysis of agricultural products quality. Transactions of the Chinese Society of Agricultural Engineering 29, 284–292.

Hu, M.-H., Dong, Q.-L., Liu, B.-L., Pan, L.-Q., Walshaw, J., 2015a. Image segmentation of bananas in a crate using a multiple threshold method. J. Food Process Eng. 2016, 427–432.

Hu, M.H., Dong, Q.L., Liu, B.L., Opara, U.L., Chen, L., 2015b. Estimating blueberry mechanical properties based on random frog selected hyperspectral data. Postharvest Biol. Technol. 106, 1–10.

Hu, M.-H., Dong, Q.-L., Liu, B.-L., Opara, U.L., 2016. Prediction of mechanical properties of blueberry using hyperspectral interactance imaging. Postharvest Biol. Technol. 115, 122–131.

Hu, M.-H., Zhai, G.-T., Li, D., Fan, Y.-Z., Chen, X.-H., Yang, X.-K., 2017. Synergetic use of thermal and visible imaging techniques for contactless and unobtrusive breathing measurement. J. Biomed. Opt. 22, 036006.

Hu, M.-H., Zhao, Y., Zhai, G.-T., 2018a. Active learning algorithm can establish classifier of blueberry damage with very small training dataset using hyperspectral transmittance data. Chemom. Intell. Lab. Syst. 172, 52–57.

Hu, M., Zhai, G., Li, D., Li, H., Liu, M., Tang, W., Chen, Y., 2018b. Influence of image resolution on the performance of remote breathing rate measurement using thermal imaging technique. Infrared Phys. Technol. 93, 63–69.

Hu, M.H., Zhai, G.T., Zhao, Y., Wang, Z.D., 2018c. Uses of selection strategies in both spectral and sample spaces for classifying hard and soft blueberry using near infrared data. Sci. Rep. 8, 6671.

Huang, L., Wu, D., Jin, H., Zhang, J., He, Y., Lou, C., 2011. Internal quality determination of fruit with bumpy surface using visible and near infrared spectroscopy and chemometrics: a case study with mulberry fruit. Biosyst. Eng. 109, 377–384.

Hyeon, P., Eun, J., Se-Han, K., 2018. Crops disease diagnosing using image-based deep learning mechanism. IEEE International Conference on Computing and Network Communications, pp. 23–26.

Intaravanne, Y., Sumriddetchkajorn, S., 2015. Android-based rice leaf color analyzer for estimating the needed amount of nitrogen fertilizer. Comput. Electron. Agric. 116, 228–233.

Intaravanne, Y., Sumriddetchkajorn, S., Nukeaw, J., 2012. Cell phone-based two-dimensional spectral analysis for banana ripeness estimation. Sensors Actuators B Chem. 168, 390–394.

Jiang, J.-A., Chang, H.-Y., Wu, K.-H., Ouyang, C.-S., Yang, M.-M., Yang, E.-C., Chen, T.-W., Lin, T.-T., 2008. An adaptive image segmentation algorithm for X-ray quarantine inspection of selected fruits. Comput. Electron. Agric. 60, 190–200.

Jiang, Y., Li, C., Takeda, F., 2016. Nondestructive detection and quantification of blueberry bruising using near-infrared (NIR) hyperspectral reflectance imaging. Sci. Rep. 6, 35679.

Kartal, S., Aday, M.S., Caner, C., 2012. Use of microperforated films and oxygen scavengers to maintain storage stability of fresh strawberries. Postharvest Biol. Technol. 71, 32–40.

Kelkar, S., Boushey, C.J., Okos, M., 2015. A method to determine the density of foods using X-ray imaging. J. Food Eng. 159, 36–41.

Kim, S.W., Min, S.R., Kim, J., Park, S.K., Kim, T.I., Liu, J.R., 2009. Rapid discrimination of commercial strawberry cultivars using Fourier transform infrared spectroscopy data combined by multivariate analysis. Plant Biotechnology Reports 3, 87–93.

Kuzy, J., Jiang, Y., Li, C., 2018. Blueberry bruise detection by pulsed thermographic imaging. Postharvest Biol. Technol. 136, 166–177.

Lamb, N., Mooi Choo, C., 2018. A Strawberry Detection System Using Convolutional Neural Networks.

Leiva-Valenzuela, G.A., Aguilera, J.M., 2013. Automatic detection of orientation and diseases in blueberries using image analysis to improve their postharvest storage quality. Food Control 33, 166–173.

Leiva-Valenzuela, G.A., Lu, R., Miguel Aguilera, J., 2013. Prediction of firmness and soluble solids content of blueberries using hyperspectral reflectance imaging. J. Food Eng. 115, 91–98.

Leiva-Valenzuela, G.A., Lu, R., Aguilera, J.M., 2014. Assessment of internal quality of blueberries using hyperspectral transmittance and reflectance images with whole spectra or selected wavelengths. Innovative Food Sci. Emerg. Technol. 24, 2–13.

Li, X.L., He, Y., 2006. Non-destructive measurement of acidity of Chinese bayberry using Vis/NIRS techniques. Eur. Food Res. Technol. 223, 731–736.

Li, X.L., He, Y., Fang, H., 2007. Non-destructive discrimination of Chinese bayberry varieties using Vis/NIR spectroscopy. J. Food Eng. 81, 357–363.

Li, C., Luo, J., MacLean, D., 2011. A novel instrument to delineate varietal and harvest effects on blueberry fruit texture during storage. J. Sci. Food Agric. 91, 1653–1658.

Li, H., Lee, W.S., Wang, K., 2014. Identifying blueberry fruit of different growth stages using natural outdoor color images. Comput. Electron. Agric. 106, 91–101.

Li, F., Liu, Z., Sun, T., Ma, Y., Ding, X., 2015. Confocal three-dimensional micro X-ray scatter imaging for non-destructive detecting foreign bodies with low density and low-Z materials in food products. Food Control 54, 120–125.

Li, D., Zhang, X.-P., Hu, M., Zhai, G., Yang, X., 2018. Physical password breaking via thermal sequence analysis. IEEE Transactions on Information Forensics and Security 14, 1142–1154.

Liu, J.J., Li, Z., 2014. The terahertz spectrum detection of transgenic food. Optik 125, 6867–6869.

Liu, C.H., Liu, W., Lu, X.Z., Ma, F., Chen, W., Yang, J.B., Zheng, L., 2014. Application of multispectral imaging to determine quality attributes and ripeness stage in strawberry fruit. PLoS One 9, e87818.

Liu, L.X., Wang, Y.F., Gao, C.M., Huan, H.T., Zhao, B.X., Yan, L.J., 2015. Photoacoustic spectroscopy as a non-destructive tool for quantification of pesticide residue in apple cuticle. Int. J. Thermophys. 36, 868–872.

Liu, Q., Sun, K., Peng, J., Xing, M., Pan, L., Tu, K., 2018. Identification of bruise and fungi contamination in strawberries using hyperspectral imaging technology and multivariate analysis. Food Anal. Methods 11, 1518–1527.

Liu, Q., Wei, K., Xiao, H., Tu, S., Sun, K., Sun, Y., Pan, L., Tu, K., 2019. Near-infrared hyperspectral imaging rapidly detects the decay of postharvest strawberry based on water-soluble sugar analysis. Food Anal. Methods 12, 936–946.

Lopez-Ruiz, N., Curto, V.F., Erenas, M.M., Benito-Lopez, F., Diamond, D., Palma, A.J., Capitan-Vallvey, L.F., 2014. Smartphone-based simultaneous pH and nitrite colorimetric determination for paper microfluidic devices. Anal. Chem. 86, 9554–9562.

Lu, Y., Lu, R., 2017. Non-destructive defect detection of apples by spectroscopic and imaging technologies: a review. Trans. ASABE 60, 1765–1790.

Lu, H.F., Zheng, H., Hu, Y., Lou, H.Q., Kong, X.C., 2011. Bruise detection on red bayberry (Myrica rubra Sieb. & Zucc.) using fractal analysis and support vector machine. J. Food Eng. 104, 149–153.

Lu, Y., Du, C., Yu, C., Zhou, J., 2015. Determination of nitrogen in rapeseed by Fourier transform infrared photoacoustic spectroscopy and independent component analysis. Anal. Lett. 48, 1150–1162.

Magwaza, L.S., Opara, U.L., 2014. Investigating non-destructive quantification and characterization of pomegranate fruit internal structure using X-ray computed tomography. Postharvest Biol. Technol. 95, 1–6.

Magwaza, L.S., Opara, U.L., Nieuwoudt, H., Cronje, P.J.R., Saeys, W., Nicolai, B., 2012. NIR spectroscopy applications for internal and external quality analysis of citrus fruit-a review. Food Bioprocess Technol. 5, 425–444.

Mahajan, S., Das, A., Sardana, H.K., 2015. Image acquisition techniques for assessment of legume quality. Trends Food Sci. Technol. 42, 116–133.

Manganaris, G.A., Goulas, V., Vicente, A.R., Terry, L.A., 2014. Berry antioxidants: small fruits providing large benefits. J. Sci. Food Agric. 94, 825–833.

Manley, M., 2014. Near-infrared spectroscopy and hyperspectral imaging: non-destructive analysis of biological materials. Chem. Soc. Rev. 43, 8200–8214.

Markovic, I., Markovic, D., Ilic, J., Simonovic, V., Veg, E., Sinikovic, G., Gubeljak, N., 2018. Application of statistical indicators for digital image analysis and segmentation in sorting of agriculture products. Tehnicki Vjesnik-Technical Gazette 25, 1739–1745.

Martynenko, A., 2014. True, particle, and bulk density of shrinkable biomaterials: evaluation from drying experiments. Dry Technology 32, 1319–1325.

Masawat, P., Harfield, A., Namwong, A., 2015. An iPhone-based digital image colorimeter for detecting tetracycline in milk. Food Chem. 184, 23–29.

Mathanker, S.K., Weckler, P.R., Bowser, T.J., 2013a. X-ray applications in food and agriculture: a review. Trans. ASABE 56, 1227–1239.

Mathanker, S.K., Weckler, P.R., Wang, N., 2013b. Terahertz (THz) applications in food and agriculture: a review. Trans. ASABE 56, 1213–1226.

Matiacevich, S., Silva, P., Enrione, J., Osorio, F., 2011. Quality assessment of blueberries by computer vision. 11th International Congress on Engineering and Food. vol. 1, pp. 421–425.

Meinlschmidt, P., Margner, V., 2002. Detection of foreign substances in food using thermography. In: Maldague, X.P., Rozlosnik, A.E. (Eds.), Thermosense Xxiv. Spie-Int Soc Optical Engineering, Bellingham, pp. 565–571.

Meralitimes, Z., 2015. Super vision. Nature 518, 158–160.

Meyer, A.C., Eifert, J., Wang, H.J., Sanglay, G., 2018. Volume estimation of strawberries, mushrooms, and tomatoes with a machine vision system. Int. J. Food Prop. 21, 1867–1874.

Mollazade, K., Omid, M., Tab, F.A., Mohtasebi, S.S., 2012. Principles and applications of light backscattering imaging in quality evaluation of agro-food products: a review. Food Bioprocess Technol. 5, 1465–1485.

Mulone, C., Budini, N., Vincitorio, F.M., Freyre, C., Diaz, A.J.L., Rego, A.R., 2013. Analysis of strawberry ripening by dynamic speckle measurements. 8th Iberoamerican Optics Meeting and 11th Latin American Meeting on Optics, Lasers, and Applications. vol. 8785.

Munera, S., Blasco, J., Amigo, J.M., Cubero, S., Talens, P., Aleixos, N., 2019. Use of hyperspectral transmittance imaging to evaluate the internal quality of nectarines. Biosyst. Eng. 182, 54–64.

Nanyam, Y., Choudhary, R., Gupta, L., Paliwal, J., 2012. A decision-fusion strategy for fruit quality inspection using hyperspectral imaging. Biosyst. Eng. 111, 118–125.

Nguyen Do Trong, N., Erkinbaev, C., Tsuta, M., De Baerdemaeker, J., Nicolaï, B., Saeys, W., 2014a. Spatially resolved diffuse reflectance in the visible and near-infrared wavelength range for non-destructive quality assessment of 'Braeburn' apples. Postharvest Biol. Technol. 91, 39–48.

Nguyen Do Trong, N., Rizzolo, A., Herremans, E., Vanoli, M., Cortellino, G., Erkinbaev, C., Tsuta, M., Spinelli, L., Contini, D., Torricelli, A., Verboven, P., De Baerdemaeker, J., Nicolaï, B., Saeys, W., 2014b. Optical properties–microstructure–texture relationships of dried apple slices: spatially resolved diffuse reflectance spectroscopy as a novel technique for analysis and process control. Innovative Food Sci. Emerg. Technol. 21, 160–168.

Nicolai, B.M., Beullens, K., Bobelyn, E., Peirs, A., Saeys, W., Theron, K.I., Lammertyn, J., 2007. Nondestructive measurement of fruit and vegetable quality by means of NIR spectroscopy: a review. Postharvest Biol. Technol. 46, 99–118.

Nielsen, M.S., Lauridsen, T., Christensen, L.B., Feidenhans'l, R., 2013. X-ray dark-field imaging for detection of foreign bodies in food. Food Control 30, 531–535.

Nielsen, M.S., Christensen, L.B., Feidenhans'l, R., 2014. Frozen and defrosted fruit revealed with X-ray dark-field radiography. Food Control 39, 222–226.

Nishizawa, T., Mori, Y., Fukushima, S., Natsuga, M., Maruyama, Y., 2009. Non-destructive analysis of soluble sugar components in strawberry fruits using near-infrared spectroscopy. Journal of the Japanese Society for Food Science and Technology-Nippon Shokuhin Kagaku Kogaku Kaishi 56, 229–235.

Ok, G., Park, K., Kim, H.J., Chun, H.S., Choi, S.-W., 2014. High-speed terahertz imaging toward food quality inspection. Appl. Opt. 53, 1406–1412.

Ok, G., Park, K., Chun, H.S., Chang, H.-J., Lee, N., Choi, S.-W., 2015. High-performance sub-terahertz transmission imaging system for food inspection. Biomedical Optics Express 6, 1929–1941.

Oliveira, L., Costa, V., Neves, G., Oliveira, T., Jorge, E., Lizarraga, M., 2014. A mobile, lightweight, poll-based food identification system. Pattern Recogn. 47, 1941–1952.

de Oliveira, E.M., Leme, D.S., Groenner Barbosa, B.H., Rodarte, M.P., Fonseca Alvarenga Pereira, R.G., 2016. A computer vision system for coffee beans classification based on computational intelligence techniques. J. Food Eng. 171, 22–27.

Oo, L.M., Aung, N.Z., 2018. A simple and efficient method for automatic strawberry shape and size estimation and classification. Biosyst. Eng. 170, 96–107.

Opara, U.L., Pathare, P.B., 2014. Bruise damage measurement and analysis of fresh horticultural produce—a review. Postharvest Biol. Technol. 91, 9–24.

Pan, L., Lu, R., Zhu, Q., Tu, K., Cen, H., 2016. Predict compositions and mechanical properties of sugar beet using hyperspectral scattering. Food Bioprocess Technol. 9, 1177–1186.

Patel, R.K., Jain, K.R., Patel, T.R., 2013. Non-destructive quality evaluation technique for processed Phyllanthus emblica (gooseberry) using image processing. In: Tomar, G.S., Dixit, M., Wang, F.Z. (Eds.), 2013 International Conference on Communication Systems and Network Technologies. IEEE, New York, pp. 69–73.

Pertot, I., Kuflik, T., Gordon, I., Freeman, S., Elad, Y., 2012. Identificator: a web-based tool for visual plant disease identification, a proof of concept with a case study on strawberry. Comput. Electron. Agric. 84, 144–154.

Peshlov, B.N., Dowell, F.E., Drummond, F.A., Donahue, D.W., 2009. Comparison of three near infrared spectro photo meters for infestation detection in wild blueberries using multivariate calibration models. J. Near Infrared Spectrosc. 17, 203–212.

Pongnumkul, S., Chaovalit, P., Surasvadi, N., 2015. Applications of smartphone-based sensors in agriculture: a systematic review of research. Journal of Sensors 2015, 1–18.

Popa, C., Dumitras, D.C., Patachia, M., Banita, S., 2014. Testing fruit quality by photoacoustic spectroscopy assay. Laser Phys. 24, 105702.

Preechaburana, P., Suska, A., Filippini, D., 2014. Biosensing with cell phones. Trends Biotechnol. 32, 351–355.

Pu, Y.-Y., Feng, Y.-Z., Sun, D.-W., 2015. Recent progress of hyperspectral imaging on quality and safety inspection of fruits and vegetables: a review. Compr. Rev. Food Sci. Food Saf. 14, 176–188.

Qin, J., Chao, K., Kim, M.S., 2012. Nondestructive evaluation of internal maturity of tomatoes using spatially offset Raman spectroscopy. Postharvest Biol. Technol. 71, 21–31.

Qin, J.Y., Ying, Y.B., Xie, L.J., 2013. The detection of agricultural products and food using terahertz spectroscopy: a review. Appl. Spectrosc. Rev. 48, 439–457.

Qin, J.Y., Xie, L.J., Ying, Y.B., 2015. Determination of tetracycline hydrochloride by terahertz spectroscopy with PLSR model. Food Chem. 170, 415–422.

Rakow, N.A., Suslick, K.S., 2000. A colorimetric sensor array for odour visualization. Nature 406, 710–713.

Sanchez, M.-T., Jose De la Haba, M., Benitez-Lopez, M., Fernandez-Novales, J., Garrido-Varo, A., Perez-Marin, D., 2012. Non-destructive characterization and quality control of intact strawberries based on NIR spectral data. J. Food Eng. 110, 102–108.

Seeram, N.P., Adams, L.S., Zhang, Y., Lee, R., Sand, D., Scheuller, H.S., Heber, D., 2006. Blackberry, black raspberry, blueberry, cranberry, red raspberry, and strawberry extracts inhibit growth and stimulate apoptosis of human cancer cells in vitro. J. Agric. Food Chem. 54, 9329–9339.

Shao, Y., He, Y., 2008. Nondestructive measurement of acidity of strawberry using Vis/NIR spectroscopy. Int. J. Food Prop. 11, 102–111.

Shao, Y.N., He, Y., Mao, J.Y., 2007. Quantitative analysis of bayberry juice acidity based on visible and near-infrared spectroscopy. Appl. Opt. 46, 6391–6396.

Shen, F., Zhang, B., Cao, C.J., Jiang, X.S., 2018. On-line discrimination of storage shelf-life and prediction of post-harvest quality for strawberry fruit by visible and near infrared spectroscopy. J. Food Process Eng. 41, e12866.

Shi, J.-Y., Zou, X.-B., Zhao, J.-W., Mao, H.-P., 2011. Selection of wavelength for strawberry NIR spectroscopy based on BiPLS combined with SAA. Journal of Infrared and Millimeter Waves 30, 458–462.

Shiraga, K., Ogawa, Y., Kondo, N., Irisawa, A., Imamura, M., 2013. Evaluation of the hydration state of saccharides using terahertz time-domain attenuated total reflection spectroscopy. Food Chem. 140, 315–320.

Siedliska, A., Baranowski, P., Zubik, M., Mazurek, W., Sosnowska, B., 2018. Detection of fungal infections in strawberry fruit by VNIR/SWIR hyperspectral imaging. Postharvest Biol. Technol. 139, 115–126.

Sinelli, N., Spinardi, A., Di Egidio, V., Mignani, I., Casiraghi, E., 2008. Evaluation of quality and nutraceutical content of blueberries (Vaccinium corymbosum L.) by near and mid-infrared spectroscopy. Postharvest Biol. Technol. 50, 31–36.

Sinelli, N., Casiraghi, E., Barzaghi, S., Brambilla, A., Giovanelli, G., 2011. Near infrared (NIR) spectroscopy as a tool for monitoring blueberry osmo-air dehydration process. Food Res. Int. 44, 1427–1433.

Sivertsen, A.H., Heia, K., Hindberg, K., Godtliebsen, F., 2012. Automatic nematode detection in cod fillets (Gadus morhua L.) by hyperspectral imaging. J. Food Eng. 111, 675–681.

Sofu, M.M., Er, O., Kayacan, M.C., Cetisli, B., 2016. Design of an automatic apple sorting system using machine vision. Comput. Electron. Agric. 127, 395–405.

Sugiyama, T., Sugiyama, J., Tsuta, M., Fujita, K., Shibata, M., Kokawa, M., Araki, T., Nabetani, H., Sagara, Y., 2010. NIR spectral imaging with discriminant analysis for detecting foreign materials among blueberries. J. Food Eng. 101, 244–252.

Sumriddetchkajorn, S., Chaitavon, K., Intaravanne, Y., 2014. Mobile-platform based colorimeter for monitoring chlorine concentration in water. Sensors Actuators B Chem. 191, 561–566.

Tan, K., Lee, W.S., Gan, H., Wang, S., 2018. Recognising blueberry fruit of different maturity using histogram oriented gradients and colour features in outdoor scenes. Biosyst. Eng. 176, 59–72.

Uyar, R., Erdogdu, F., 2009. Potential use of 3-dimensional scanners for food process modeling. J. Food Eng. 93, 337–343.

Vadivambal, R., Jayas, D.S., 2011. Applications of thermal imaging in agriculture and food industry—a review. Food Bioprocess Technol. 4, 186–199.

Vasquez, C., Diaz-Calderon, P., Enrione, J., Matiacevich, S., 2013. State diagram, sorption isotherm and color of blueberries as a function of water content. Thermochim. Acta 570, 8–15.

Wang, W., Li, C., 2015. A multimodal machine vision system for quality inspection of onions. J. Food Eng. 166, 291–301.

Wang, Q., Wang, H., Xie, L., Zhang, Q., 2012. Outdoor color rating of sweet cherries using computer vision. Comput. Electron. Agric. 87, 113–120.

Wang, X., Huang, W., Wang, Q., Liu, C., Wang, C., Yang, G., Zhao, C., 2017a. Raman hyperspectral image analysis of benzoyl peroxide additive. J. Mol. Struct. 1138, 6–11.

Wang, X., Huang, W., Zhao, C., Wang, Q., Liu, C., Yang, G., 2017b. Quantitative analysis of BPO additive in flour via Raman hyperspectral imaging technology. Eur. Food Res. Technol. 243, 2265–2273.

Wang, X., Zhao, C., Huang, W., Wang, Q., Liu, C., Yang, G., 2017c. Effective detection of benzoyl peroxide in flour based on parameter selection of Raman hyperspectral system. Spectrosc. Lett. 50, 364–369.

Wang, Z.D., Hu, M.H., Zhai, G.T., 2018. Application of deep learning architectures for accurate and rapid detection of internal mechanical damage of blueberry using hyperspectral transmittance data. Sensors 18, 1126.

van der Werf, I., Mangone, A., Giannossa, L.C., Traini, A., Laviano, R., Coralini, A., Sabbatini, L., 2009. Archaeometric investigation of Roman tesserae from Herculaneum (Italy) by the combined use of complementary micro-destructive analytical techniques. J. Archaeol. Sci. 36, 2625–2634.

West, G.A., Barrett, J.J., Siebert, D.R., Reddy, K.V., 1983. Photoacoustic spectroscopy. Rev. Sci. Instrum. 54, 797–817.

Whitaker, V.M., Price, J.F., Peres, N.A., MacRae, A.W., Santos, B.M., Folta, K.M., Noling, J.W., 2014. Current Strawberry Research at the University of Florida. VII International Strawberry Symposium. vol. 1049 pp. 161–166.

Won-Hui, L., Wangjoo, L., 2014. Food inspection system using terahertz imaging. Microw. Opt. Technol. Lett. 56, 1211–1214.

Wu, D., Sun, D.-W., 2013. Advanced applications of hyperspectral imaging technology for food quality and safety analysis and assessment: a review — part I: fundamentals. Innovative Food Sci. Emerg. Technol. 19, 1–14.

Wu, D., Meng, L., Yang, L., Wang, J., Fu, X., Du, X., Li, S., He, Y., Huang, L., 2019. Feasibility of laser-induced breakdown spectroscopy and hyperspectral imaging for rapid detection of thiophanate-methyl residue on mulberry fruit. Int. J. Mol. Sci. 20, 1–14.

Wulf, J.S., Ruhmann, S., Rego, I., Puhl, I., Treutter, D., Zude, M., 2008. Nondestructive application of laser-induced fluorescence spectroscopy for quantitative analyses of phenolic compounds in strawberry fruits (Fragaria × ananassa). J. Agric. Food Chem. 56, 2875–2882.

Xie, L.J., Ye, X.Q., Liu, D.H., Ying, Y.B., 2009. Quantification of glucose, fructose and sucrose in bayberry juice by NIR and PLS. Food Chem. 114, 1135–1140.

Xie, L.J., Ye, X.Q., Liu, D.H., Ying, Y.B., 2011. Prediction of titratable acidity, malic acid, and citric acid in bayberry fruit by near-infrared spectroscopy. Food Res. Int. 44, 2198–2204.

Xin, L., Jun, L., Jing, T., 2018. A Deep Learning Method for Recognizing Elevated Mature Strawberries.

Xu, L., Zhao, Y., 2010. Automated strawberry grading system based on image processing. Comput. Electron. Agric. 71, S32–S39.

Xu, W., Xie, L., Ye, Z., Gao, W., Yao, Y., Chen, M., Qin, J., Ying, Y., 2015. Discrimination of transgenic rice containing the Cry1Ab protein using terahertz spectroscopy and chemometrics. Sci. Rep. 5, 11115.

Yamamoto, K., Ninomiya, S., Kimura, Y., Hashimoto, A., Yoshioka, Y., Kameoka, T., 2015. Strawberry cultivar identification and quality evaluation on the basis of multiple fruit appearance features. Comput. Electron. Agric. 110, 233–240.

Yang, C., Lee, W.S., Williamson, J.G., 2012. Classification of blueberry fruit and leaves based on spectral signatures. Biosyst. Eng. 113, 351–362.

Yoshioka, Y., Nakayama, M., Noguchi, Y., Horie, H., 2013. Use of image analysis to estimate anthocyanin and UV-excited fluorescent phenolic compound levels in strawberry fruit. Breed. Sci. 63, 211–217.

Zanini, S., Marzotto, M., Giovinazzo, F., Bassi, C., Bellavite, P., 2015. Effects of dietary components on cancer of the digestive system. Crit. Rev. Food Sci. Nutr. 55, 1870–1885.

Zareiforoush, H., Minaei, S., Alizadeh, M., Banakar, A., 2015. Potential applications of computer vision in quality inspection of rice: a review. Food Eng. Rev. 7, 321–345.

Zdunek, A., Herppich, W.B., 2012. Relation of biospeckle activity with chlorophyll content in apples. Postharvest Biol. Technol. 64, 58–63.

Zhang, R.Y., Ying, Y.B., Rao, X.Q., Li, J.B., 2012. Quality and safety assessment of food and agricultural products by hyperspectral fluorescence imaging. J. Sci. Food Agric. 92, 2397–2408.

Zhang, B., Huang, W., LiZhao, C., Jiangbo, Fan, S., Wu, J., Liu, C., 2014a. Principles, developments and applications of computer vision for external quality inspection of fruits and vegetables: a review. Food Res. Int. 62, 326–343.

Zhang, B.H., Huang, W.Q., Li, J.B., Zhao, C.J., Fan, S.X., Wu, J.T., Liu, C.L., 2014b. Principles, developments and applications of computer vision for external quality inspection of fruits and vegetables: a review. Food Res. Int. 62, 326–343.

Zhang, M., Li, C., Takeda, F., Yang, F., 2017. Detection of internally bruised blueberries using hyperspectral transmittance imaging. Trans. ASABE 60, 1489–1502.

Zhang, B., Gu, B., Tian, G., Zhou, J., Huang, J., Xiong, Y., 2018. Challenges and solutions of optical-based nondestructive quality inspection for robotic fruit and vegetable grading systems: a technical review. Trends Food Sci. Technol. 81, 213–231.

Zhang, M., Li, C., Yang, F., 2019a. Optical properties of blueberry flesh and skin and Monte Carlo multi-layered simulation of light interaction with fruit tissues. Postharvest Biol. Technol. 150, 28–41.

Zhang, Q., Zou, X., Lin, G., Sun, Y., 2019b. Image feature extraction and online grading method for weight and shape of strawberry. Journal of System Simulation 31, 7–15.