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Review

Principles, developments and applications of computer vision for external quality inspection of fruits and vegetables: A review

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ABSTRACT

Appearance is a very important sensory quality attribute of fruits and vegetables, which can influence not only their market value, consumer's preferences and choice but also their internal quality to some extent. External quality of fruits and vegetables is generally evaluated by considering their color, texture, size, shape, as well as the visual defects. External quality inspection of fruits and vegetables manually is a time-consuming and labor intensive work. Over the past decades, computer vision systems, including traditional computer vision system, hyperspectral computer vision system, and multispectral computer vision system, have been widely used in the food industry, and proved to be scientific and powerful tools for the automatic external quality inspection of food and agricultural products. Many researches based on spatial image and/or spectral image processing and analysis have been published proposing the use of computer vision technique in the field of external quality inspection of fruits and vegetables. This paper presents a detailed overview of the comparative introduction, latest developments and applications of computer vision systems in the external quality inspection of fruits and vegetables. Additionally, the principal components, basic theories, and corresponding processing and analytical methods are also reported in this paper.

Contents

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1. Introduction

External quality is the most important and direct sensory quality attribute of agricultural products. In general terms, the external quality of fruits and vegetables is evaluated by considering their color, texture, size, shape, and visual defects (Costa et al., 2011). The outer appearance of fruits and vegetables affects their point-of-sale value and consumer's buying behavior, and sometimes the defective, infected and contaminated fruits and vegetables can spread the infection or contamination to the sound products even the whole batch, thus causing great economic losses, moreover safety problems (ElMasry, Wang, Vigneault, Qiao, & ElSayed, 2008; Gomez-Sanchis, Gomez-Chova, Aleixos, Camps-Valls, Montesinos-Herrero, Molto et al., 2008; Gomez-Sanchis, Molto, Camps-Valls, Gomez-Chova, Aleixos & Blasco, 2008; Li, Rao, & Ying, 2011; Xing, Bravo, Jancsok, Ramon, & De Baerdemaeker, 2005). Therefore, external quality inspecting and grading systems in the post-harvest preprocessing stage become very important and necessary (Teena, Manickavasagan, Mothershaw, El Hadi, & Jayas, 2013).

Automatic external quality inspection of fruits and vegetables is still a challenging work. Some external quality criteria, such as color, texture, size, and shape, are actually automated on industrial graders, but grading of fruits and vegetables according to the other appearance criteria, such as bruises, rottenness, and some other unobvious defects which present the same color and texture to the sound peel, or defects which are always confused with the stem-end and calyxes, is not yet efficient and consequently remains a manual operation (Leemans & Destain, 2004). Manual operation has some drawbacks such as inconsistency, time consuming, variability and subjectivity, besides, the manual process is also very tedious, laborious, costly, and easily influenced by the surrounding environment (ElMasry, Cubero, Molto, & Blasco, 2012; Elmasry, Kamruzzaman, Sun, & Allen, 2012; Razmjooy, Mousavi, & Soleymani, 2012). So it is urgent and necessary to develop an automatic external quality inspection system to replace manual inspection.

Due to the fact that most part of the external quality attributes is currently inspected visually, computer vision provides a means to perform this task automatically (Aleixos, Blasco, Navarron, & Molto, 2002). Computer vision is an engineering technology that combines mechanics, optical instrumentation, electromagnetic sensing, digital video and image processing technology (Patel, Kar, Jha, & Khan, 2012). And it is the science responsible for the study and application of methods which enable a computer to understand the content of an image, and this interpretation involves the extraction of certain characteristics which are important for a given aim (Gomes & Leta, 2012). Over the past decades, with the rapid development of information science, image processing and pattern recognition technology, as well as computer hardware and software, computer vision has been developed as a scientific inspection tool for quality and safety of a variety of food and agricultural products. In the automatic external quality inspection, this technology aims to duplicate the effect of the human vision by electronically perceiving and understanding an image (Brosnan & Sun, 2002), recognize and interpret the external characters of fruits and vegetables, and provide the information for the external quality sorting and grading machine.

The most common computer vision system for external quality inspection is traditional computer vision system which is based on RGB color video cameras that imitate the vision of the human eyes by capturing images using three filters centered at red (R), green (G) and blue (B) wavelengths (Lorente et al., 2012). Most external quality characteristics, such as color, texture, size, shape, and some obvious defects, can be measured or detected by using the traditional computer vision system. But for some unobvious defects, it is impossible or difficult to detect by using the traditional computer vision system for lack of spectral and multi-constituent information in conventional color images. With the help of wavelength dispersive devices, high resolution cameras, as well as the recent advances in hardware and software of a computer, multispectral and hyperspectral computer vision systems have been developed as efficient inspection tools for the quality and safety of a variety of agricultural products. A typical spectral image is composed of a set of monochromatic images corresponding to certain wavelengths, and hyperspectral and multispectral computer vision systems have the natural advantage compared to the traditional computer vision, even the human vision. The extensive spectral and imaging information acquired by the hyperspectral and multispectral computer vision systems makes it possible to extract or discover some appearance features that are impossible or difficult with the traditional computer vision system. Lots of successful applications have proven the multispectral and hyperspectral computer vision systems to be outstanding tools in fruit and vegetable external quality characteristics, especially for chilling injury, bruise and some other unobvious defect inspection.

Several review papers have been published (Davies, 2009; Feng & Sun, 2012; Liu, Zeng, & Sun, 2013; Qin, Chao, Kim, Lu, & Burks, 2013), some of them are only focused on traditional computer vision system in external quality inspection, while others are focused on hyperspectral and multispectral imaging in quality (external, internal and safety) evaluation. A detailed summarization of principles, developments and applications of three popular computer vision systems in fruit and vegetable external quality inspection is not available. Therefore, the main objectives of this paper are to give a contrastive introduction of three different computer vision systems, and review the basic principles, latest developments and applications of computer vision in external quality inspection of fruits and vegetables. Additionally, the principle components, basic theories, and corresponding processing and analysis methods are also reported.

2. Construction of computer vision systems

Fig. 1 shows the configuration of a typical computer vision system. As shown in Fig. 1 a computer vision system generally consists of the following five basic components: illumination, a camera, an image capture board (frame grabber or digitizer), and computer hardware

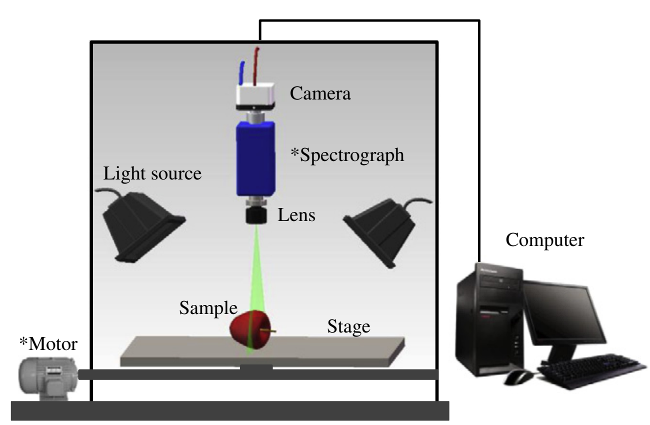

Fig. 1. A schematic of a typical computer vision system. *Just for hyperspectral and multispectral computer vision systems.

and software (Wang & Sun, 2002). Additionally, a wavelength dispersion device (spectrograph or filter) and a transportation stage are additional components of the hyperspectral or multispectral computer vision systems.

Illumination is an important component of computer vision system. As with the human eyes, vision systems are affected by the level and quality of illumination. Illumination devices generate light that illuminates the inspected target objects, therefore the performance of the illumination system can greatly influence the quality of images and plays an important role in the overall efficiency and accuracy of the system (Brosnan & Sun, 2002; Brosnan & Sun, 2004; Novini & Engineers, 1995). Good illumination can help to improve the success of the image processing and analysis by reducing noise, shadow, reflection, and enhancing image contrast. In the external quality inspection of fruits and vegetables, the illumination systems are mainly two different arrangements: front lighting and back lighting. Front lighting (electron projection lithography or reflective illumination) is mainly used in situations where the surface quality characteristics are to be inspected such as color, texture, as well as the skin defects. However, the back lighting (transmitted illumination) is always used in situations where the edge or boundary quality characteristics are to be inspected such as size and shape. The positions, types of lamps, and color quality of the illumination are all considered when choosing the most suitable illumination (Teena et al., 2013). Incandescent lamps, fluorescent lamps, lasers, and infrared lamps are the commonly used light sources (Kodagali, 2012).

The camera, which has the same functions as the human eyes, is the key component of computer vision systems. Common image acquisition equipments used in food applications are the camera, magnetic resonance imaging (MRI), ultrasound, computed tomography (CT) and electrical tomography (Du & Sun, 2004). Charged coupled device (CCD) and complementary metal oxide semiconductor (CMOS) image sensors are two different means to generate the image digitally. A computer vision system consisting of a high resolution CCD camera and associated hardware is one of the most widely used inspection systems in the external quality inspection of food and agricultural products. Area and line scan modes are the most common scan mode of CCD cameras in inspection tasks. Array or area scan type cameras consist of a matrix of minute photosensitive elements (photo sites) from which the complete image of the object is obtained based on output proportional to the amount of incident light (Brosnan & Sun, 2002). However the line scan type cameras consist of only a single line of photo sites, only a line image of the object is obtained at one time, therefore a transportation stage is used to move the sample under the line scan camera to get the complete image line by line.

The image capture board, or frame grabber, is an electronic device in computer vision system which is usually used to capture the individual, digital still frames from video cameras, and then displayed, stored in raw or compressed digital form.

The computer hardware and software, which imitates the human brain, is another key component of computer vision system. In the external quality of fruits and vegetables, the computer hardware and software processes and analyzes the image and gives the final inspection information about the object, and finally controls the whole inspection system to complete the grading and sorting tasks.

Wavelength dispersion devices are the core components of the hyperspectral and multispectral computer vision systems. They are used for dispersing broadband light into different wavelengths and projecting the light to an area detector. Prism, gratings and filter are three widely used wavelength dispersion devices. The principles of prism and diffraction grating are illustrated in Fig. 2. All the three types of wavelength dispersion devices can be attached to a lens and area camera to form a line- or area-scan spectral camera system. In general, prism and diffraction grating are always used in the hyperspectral computer vision system, and filters are widely used in the multispectral computer vision system.

3. Computer vision systems

Traditional, hyperspectral and multispectral computer vision systems are three most widely used vision systems in the external quality inspection of food and agricultural products. Every system has its advantages and disadvantages. The brief histories, principles, advantages and disadvantages of three different computer vision systems will be given in the following sections.

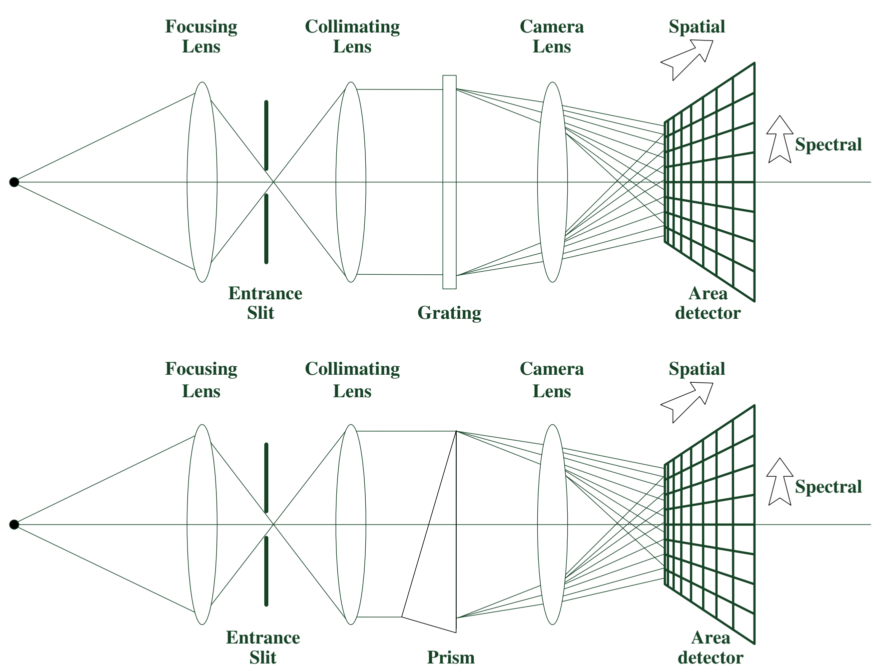

Fig. 2. Operating principles of diffraction grating and prism.

3.1. Traditional computer vision system

Traditional computer vision (or, traditional machine vision) is a young discipline with its origin traced back to the 1960s. Following an explosion of interest during the 1970s, it has experienced continued growth in both theory and application (Baxes, 1994; Patel et al., 2012). Nowadays, traditional computer vision system is widely used in medical imaging, industrial automation, security monitoring, military applications, aerospace field, intelligent transportation system, food quality and safety inspection, autonomous vehicle and robot guidance, etc.

As the human eyes are sensitive to the primary colors — red, green and blue, the traditional computer vision system is normally based on RGB color cameras that imitate the vision of the human eyes by capturing images using three filters centered at red, green and blue (RGB) wavelengths (Lorente et al., 2012). So the images captured by RGB color cameras are very close to the actual scenes perceived by the human eyes in color. Fig. 3 shows a color image of a peach, and its R, G and B component monochromatic images.

Most external quality attributes, such as color, texture, size, shape, and some obvious defects, can be inspected and graded automatically with traditional computer vision system. However, due to lack of spectral and multi-constituent information in conventional color images, some other unobvious defects, whose color and texture are similar to the sound skin, are still impossible or difficult to detect automatically only by using traditional computer vision system.

3.2. Hyperspectral computer vision system

Unlike the traditional computer vision system, which can only capture three monochromatic images centered at 700.0 nm (red, R), 546.1 nm (green, G) and 435.8 nm (blue, B) to imitate the vision of humans, hyperspectral computer vision system, or hyperspectral imaging system, integrates both spectroscopic and imaging techniques into one system to get a set of monochromatic images at almost continuous hundreds of thousands of wavelengths. Therefore, the integrated system can provide spatial information, the same as conventional imaging system, along with spectral information, the same as spectroscopic devices, for every pixel of the spatial image. The data structure of hyperspectral image is commonly called hypercube, or data cube, and can be viewed as a stack of two-dimensional images at different wavelengths, or a set of spectrums of each pixel in one two-dimensional image cluster together. Fig. 4 shows the conceptual view of a hyperspectral image of an apple with rottenness.

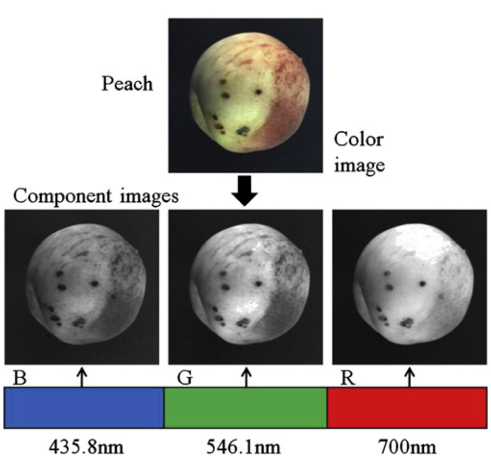

Fig. 3. A RGB color image of a peach and its component images.

In general, point scanning, line scanning and area scanning approaches are three commonly used methods to acquire the hyperspectral image cube. The three approaches are illustrated conceptually in Fig. 5.

The most advantage of hyperspectral computer vision system is the extensive information the hyperspectral image contained. Some external quality characters, such as rottenness, early bruises, and some other defects, are always unobvious in the conventional digital images, even not visible to the human eyes, therefore it is impossible or difficult to detect. Different from the conventional RGB images, whose spectrum information is very limited, the hyperspectral images contain hundreds of thousands of monochromatic images in the spectral domain. The unobvious external quality characters might be very clear or easy to detect in one single or several monochromatic images. However, the extensive information also brings some drawbacks, such as long time consuming of image acquiring, as well as the complexity of image processing and analyzing. Therefore hyperspectral computer vision system is always used to acquire images with high spatial and spectral resolutions for some fundamental researches, such as selecting the most efficient wavelengths to develop multispectral computer vision system for food quality real-time inspection.

3.3. Multispectral computer vision system

Multispectral computer vision system, or multispectral imaging system, is different from hyperspectral imaging system in the number of the monochromatic images in the spectral domain. In general, multispectral imaging is a form of imaging that involves capturing two or more different waveband monochromatic images in the spectrum. To some extent, a traditional RGB camera could be considered as a particular case of a multispectral imaging system. But unlike the conventional digital camera capturing the specific frequency light that falls on the detector in a fashion that resembles the human perception of color, multispectral computer vision system enables us to capture two or more certain single-band monochromatic images freely as we want with the narrowband filters. Fig. 6 shows the conceptual view of a multispectral image of a peach with spot defects.

The biggest advantage of the multispectral computer vision system is that the wavelengths of the monochromatic images captured can be chosen freely by using the narrowband filters. Generally, in the external quality inspection of fruits and vegetables, the hyperspectral computer vision system is used for the fundamental researches, and selecting the most efficient wavelengths to detect certain quality characters which are unobvious in the RGB images, then a multispectral computer vision system with the specific filters is developed to capture the monochromatic images in the efficient wavelengths to fulfill the real-time inspection task. One disadvantage is that the multispectral imaging system is always built by ourselves according to the specific imaging task. Image distortion and misalignment usually occur because of the camera lens distortion, camera positional tolerance etc. High-precision multispectral imaging system needs to be repeatedly checked, calibrated and debugged by analyst. Therefore developing a successful multispectral computer vision system is far from easy.

Large number of successful food quality inspection applications has proven that, hyperspectral computer vision system is mainly used for mechanism researches and selecting efficient wavelengths, and traditional and multispectral computer vision system are used for the fast in-line applications. Once the in-line inspection system has been developed, external quality inspection becomes a problem of image processing, analysis and classification.

4. Hyperspectral image processing and analysis techniques

The processing and analysis of hyperspectral images are different from that of RGB images or monochromatic images. According to the data structure of the hyperspectral image, a hyperspectral image can be considered to be either a set of two-dimensional spatial monochromatic

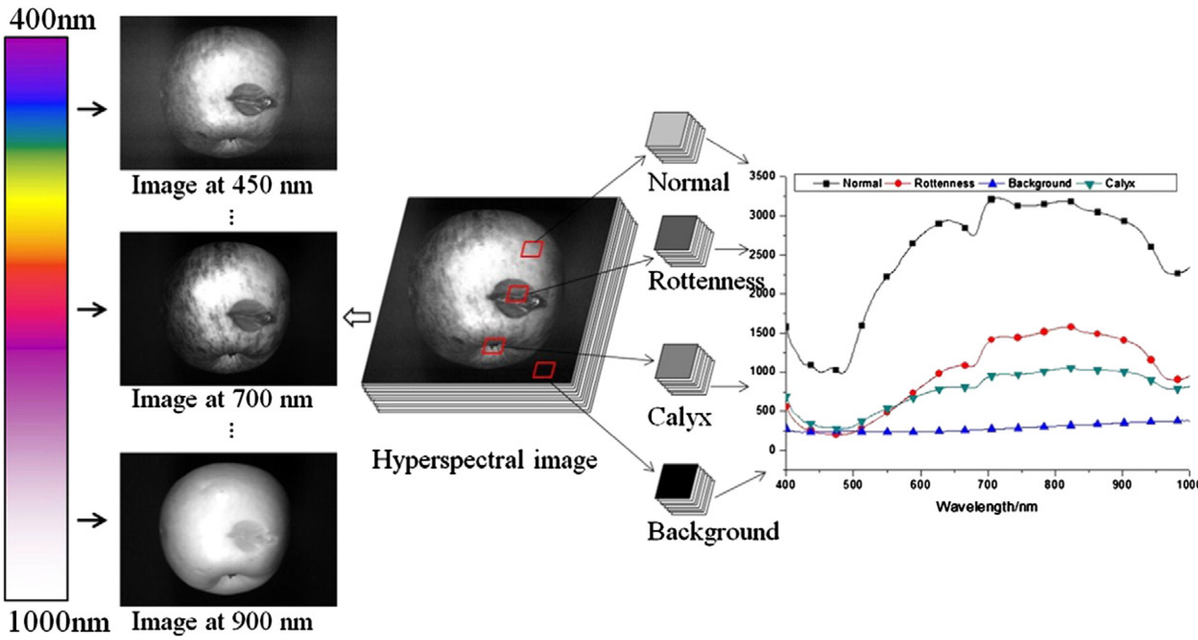

Fig. 4. Conceptual view of a hyperspectral image of an apple with rottenness.

images at each individual wavelength of the full spectrum, or a cluster of spectrums at each individual pixel of the spatial image. Therefore, the processing and analysis of hyperspectral image can be conducted in the spatial domain, spectral domain or the combination of the two domains. Generally, the main steps of processing and analysis are illustrated as Fig. 7.

Image correction and efficient wavelength selection are the most two essential steps in the processing and analysis of hyperspectral images. Image correction can ensure the stability of the hyperspectral computer vision system, and efficient wavelength selection is the important step to realize the in-line inspection by reducing the image acquiring and processing times. In this section, the methods about hyperspectral image correction and the efficient wavelength selection will be addressed in detail.

4.1. Image correction

Hyperspectral computer vision system is commonly carried out in one of the three familiar modes: reflectance, transmittance or scatter modes. In the external quality inspection of fruits and vegetables, the

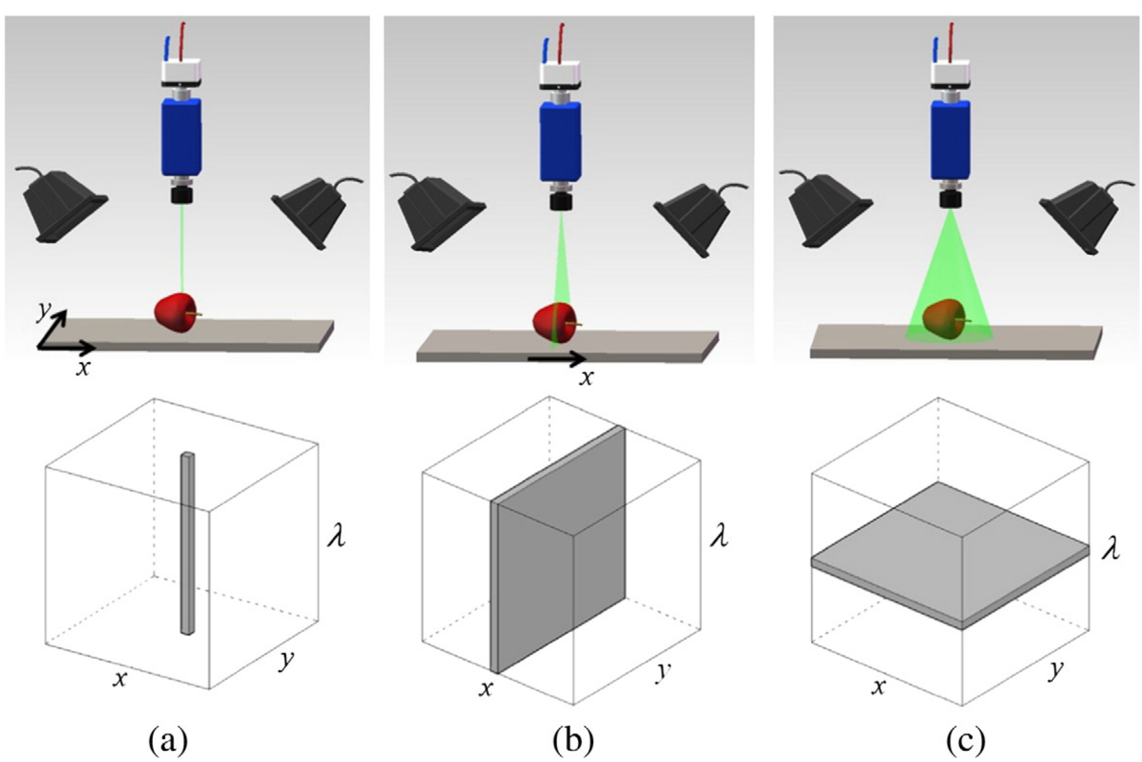

Fig. 5. Three different types of scanning modes to generate a hyperspectral image. (a) Point scanning approach. (b) Line scanning approach. (c) Area scanning approach.

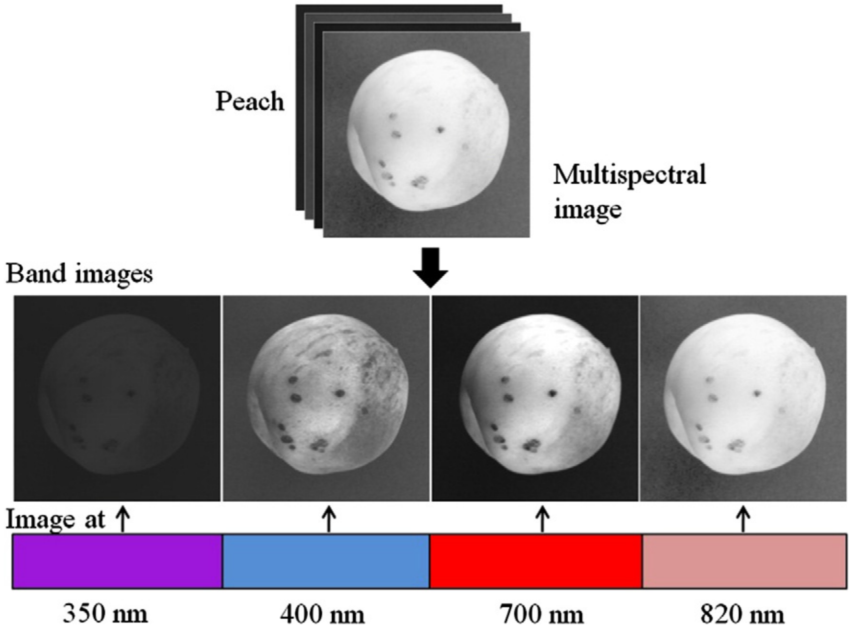

Fig. 6. Conceptual view of a multispectral image of a peach with spot defects.

reflectance mode is the most widely used acquisition mode. The raw hyperspectral image of the fruits and vegetables can be acquired and recorded in uncorrected radiance with the hyperspectral imaging system.

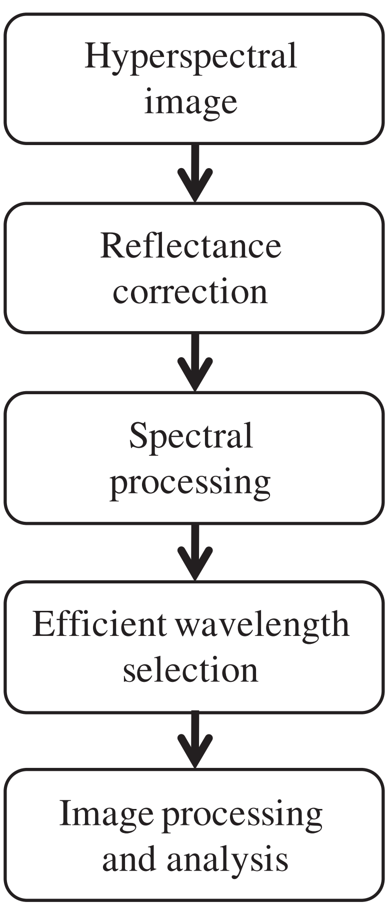

Fig. 7. Schematic diagrams of hyperspectral image processing and analysis.

However, due to the background spectral response of the device, spatial variations in the intensity of the light source in different bands and the existence of the dark current in the camera, the uncorrected radiance for the different systems, even for the same system used in different times, might be very different for the same sample taken under the same condition. To enhance the comparability of the hyperspectral image data, the raw hyperspectral image always needs to be corrected or transformed into the reflectance mode using the combination of dark reference image and the radiance of light source. In order to achieve this aim, the correction can be carried out based on calculating the ratio according to the following equation (Gomez-Sanchis, Gomez-Chova et al., 2008; Gomez-Sanchis, Molto et al., 2008):

$$R_{corrected}(\lambda) = \frac{R_{raw}(\lambda) - R_{dark}(\lambda)}{I(\lambda) - R_{dark}(\lambda)} \tag{1}$$

where, $R_{corrected}(\lambda)$ is the corrected hyperspectral reflectance image, $R_{raw}(\lambda)$ is the raw radiance of inspection target, $R_{dark}(\lambda)$ is the dark reference image, and $I(\lambda)$ is the radiance of light source. The dark reference image (with ~0% reflectance), which represents the dark response of the camera, can be acquired with the light source turned off completely and the camera lens covered completely with its non-reflective opaque black cap. However, $I(\lambda)$ cannot be measured directly by the hyperspectral computer vision system. To ease the measurement, $I(\lambda)$ can be approximately replaced by the white reference image $R_{white}(\lambda)$, which can be acquired with a 99.9% reflectance Teflon white board under the same condition as the uncorrected raw image. With the dark and white reference images, the corrected hyperspectral reflectance image $R_{corrected}$ can be taken by using the following equation (ElMasry, Wang, & Vigneault, 2009; Lu & Chen, 1999):

$$R_{corrected}(\lambda) = \left(\frac{R_{raw}(\lambda) - R_{dark}(\lambda)}{R_{white}(\lambda) - R_{dark}(\lambda)}\right) \times 100\% \tag{2}$$

where, $R_{raw}(\lambda)$ is the raw radiance of inspection target, $R_{dark}(\lambda)$ is the dark reference image, and $R_{white}(\lambda)$ is the white reference image. In Eq. (2), the operation in the denominator is to eliminate the spatial non-uniformity of the light source and the subtraction in the numerator can reduce noise of the system (Feng & Sun, 2012).

Eq. (2) can correct the spatial variations of the light source in the scene, but does not take into account the variations caused by the geometry of the surface of the fruits and vegetables, since the white reference image utilized is flat (Gomez-Sanchis, Gomez-Chova et al., 2008; Gomez-Sanchis, Molto et al., 2008). A detailed geometry for correcting the reflectance intensity caused by curvature surface can be found in Qin and Lu (2008).

4.2. The efficient wavelength selection

Hyperspectral computer vision system provides extensive and redundant information about the inspection targets. In the fundamental researches, the hyperspectral imaging acquired and the inspection algorithm are very time-consuming due to the large-scale massive data. The extensive hyperspectral image is highly correlated, and not all the monochromatic images in the full spectrum are efficient in the external quality inspection tasks. To realize the in-line inspection, the transformation from the fundamental research level of hyperspectral imaging to the fast application level of multispectral imaging must be devoted. And, selecting the most efficient wavelengths for specific inspection task is the key and challenging step to complete this transformation.

For different inspection tasks, such as bruise or rottenness inspection, the most efficient wavelengths might be very different. In general, the efficient wavelengths can be selected from the raw spectrum, preprocessing spectral or some multivariate analysis (pattern recognition) techniques. Location of the wavelengths where peaks or valleys occur in the raw spectrum may be the most efficient wavelengths. Determining the efficient wavelengths directly according to the raw spectrum is the simplest way to select the efficient wavelengths. However, the peaks and valleys are not always efficient in some inspection situation due to the existing noise and baseline shifts. Therefore, spectrum preprocessing is always an essential step before selecting efficient wavelengths according to the peaks and valleys. Smoothing, derivative methods (first and second derivatives) are the most widely used preprocessing methods to improve the stability of the raw spectrum. Compared to the methods mentioned above, multivariate analysis techniques are more complex, efficient, and most widely used methods to select the efficient wavelengths. Principle Component Analysis (PCA), Independent Component Analysis (ICA), Minimum Noise Fraction (MNF), Partial Least Squares (PLS), Linear Discriminant Analysis (LDA), Stepwise Discrimination Analysis (SDA), and Artificial Neural Network (ANN) are the most commonly used multivariate analysis methods in hyperspectral image analysis, dimension reduction and efficient wavelength selection.

Some of the multivariate analysis methods mentioned above, such as PCA, ICA, and MNF, are unsupervised classification methods. Unsupervised classification methods classify the data automatically without knowing any a priori knowledge of the classes, such as the information about the class label of the data, or how many classes there are. The other multivariate analysis methods, such as LDA, SDA, and ANN, are supervised classification methods. Supervised classification methods classify the data based on the a priori knowledge of the classes. One typical multivariate analysis method of unsupervised methods will be introduced in the following sections.

PCA is a very effective data reduction and efficient wavelength selection technique for the hyperspectral images. PCA transforms hyperspectral wavelengths into sequence of component bands (PC bands) which are the linear combinations of the original bands. The first several PC band images contain the largest percentage of the original information. Therefore it is not hard to understand why the first several PC band images can illustrate main features present in the hyperspectral image (Kim et al., 2002). An example of the hyperspectral image dimension reduction and the efficient wavelength selection by using PCA method is shown in Fig. 8. The hyperspectral reflectance images of apples were acquired in the spectral region of 326–1098 nm (1000 wavelengths) with a spectral resolution of 0.8 nm for the early bruise detection. The first five PCA score images (denoted by PC1 to PC5 in Row (a)) were obtained by using the ENVI 4.6. The PC1 score image contains almost more than 90% of the original hyperspectral image information, but the PC1 score image mainly illustrates the shape, uneven illumination of the surface, and does not provide more unique features than the original hyperspectral image. In general, some unobvious defects are always very obvious in one of the PC2 to PC4 score images. For every PC score image, there exists a corresponding loading curve, which can be interpreted to the weighting coefficients of the spectra. The peaks and valleys of the loading curves indicate the dominant wavelengths (Li et al., 2011), so the loading curves could be considered to be the basis to select the efficient wavelengths (Xing et al., 2005). In the bruise detection of apples, the PC3 score image demonstrates more information of bruises on an apple, and it can provide the best discrimination between the intact and bruised surface. Therefore, five efficient wavelengths (590, 660, 720, 820, and 960 nm) were selected according to the loading curve of PC3 score image. To verify the effectivity of selected efficient wavelengths, PCA transform was conducted with the five wavelengths, the first five PCA score images obtained were denoted by PC1 to PC5 in Row (c). Results show that the bruised area is clear in PC3 score image as that of full wavelengths, and indicate that the selected wavelengths are efficient.

All of the supervised and unsupervised methods can be conducted by the professional spectral processing and analysis software or other multivariate analysis software, or hand-coded software or programs which are developed with computer programming languages, such as Visual Basic, C/C++, MATLAB, and LabVIEW.

5. Image processing and analysis techniques

Image processing and image analysis are considered to be the core of the computer vision with various algorithms and methods available to complete the specific classification and measurement (Brosnan & Sun, 2004; Kurtz et al., 2000). Image processing and analysis are performed in three levels as illustrated in Fig. 9. The low level processing, which is the basic processing of image, involves image acquisition and image preprocessing; the intermediate level processing, which is the make-or-break step in image processing and analysis, involves image segmentation, feature extraction, representation, and description; the high level processing, which is the key step of image analysis, involves recognition, interpretation and classification. The commonly used image processing and analysis techniques in the external quality inspection of fruits and vegetables will be introduced in the following sections.

5.1. Image processing

Image processing operates on images and results in images, which can improve the visibility of features and facilitate subsequent analysis. Image processing involves image preprocessing, image segmentation, and feature extraction.

Image preprocessing can improve the quality of the acquired images by increasing the contrast, removing the blur and noise, and correcting the distortion. In the external inspection of fruits and vegetables, low contrast images are always obtained due to the uneven illumination, the curvature of spherical inspection targets, and the non-linear sensitivity of CCD detectors. The image contrast can be improved by increasing the brightness levels. The frequently used methods to increase the image contrast are basic point operations (intensity mappings) and histogram equalization. The basic point operations, such as brightness inversion and brightness scaling by multiplication, improve the image contrast by stretching the brightness levels as a mapping between the input levels and output levels. Histogram equalization is a non-linear technique aimed to highlight brightness of image by flatting the histogram. Some other lightness correction or transformation methods are also used to correct the uneven contrast in the fruit and vegetables' surface, especially the central and edge of the inspection targets. In the

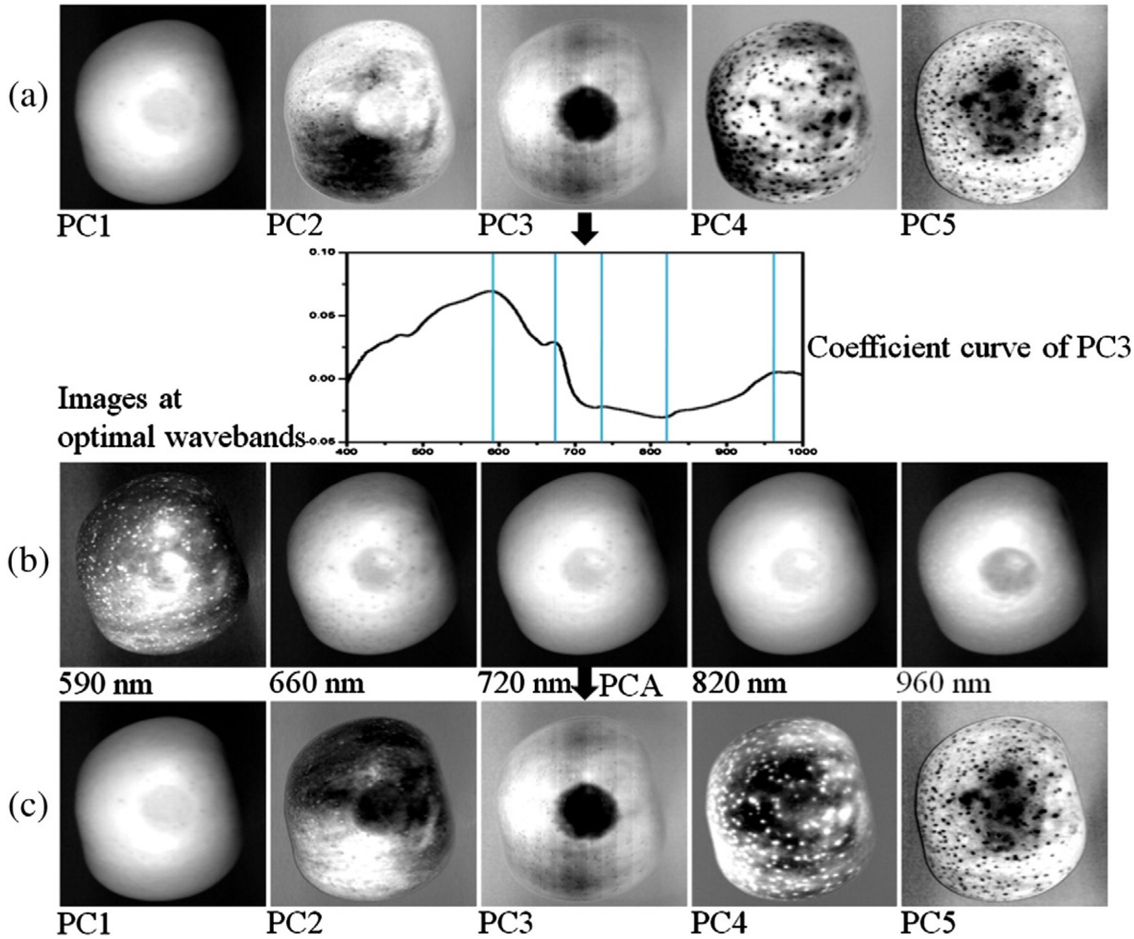

Fig. 8. Example of selecting the efficient wavelengths by using PCA method. (a) Results of PCA in the full wavelengths. (b) Images at the efficient wavelengths. (c) Results of PCA in the efficient wavelengths.

in-line inspection system, due to the rock of the system and some other uncontrollable reasons, the blur and noise are inevitable for the captured images. Some low pass filters, such as average filter, Gaussian filter, and median filter, are always used to remove the blur and noise of the captured images. Due to the images of inspection targets are captured while the targets are transported along with the conveyor belt or roller, image distortion always happens. Image distortion can be corrected with some geometric transforms, such as image translation, rotation, mirror, transpose, and scaling.

Image segmentation is a most important and challenging step aimed to divide the image into component areas or regions of interest. The subsequent image processing and analysis are highly dependent on the accuracy of image segmentation (Brosnan & Sun, 2004). Threshold-based segmentation, edge-based segmentation, region-based segmentation,

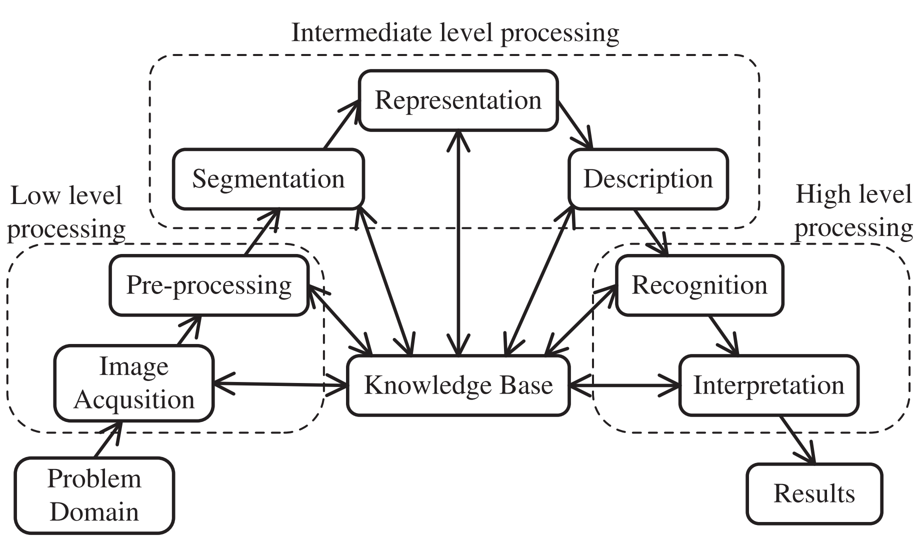

Fig. 9. Different levels of image processing (Du & Sun, 2004).

and classification-based segmentation are four major types of segmentation methods (Jackman, Sun, & Allen, 2011; Narendra & Hareesh, 2010; Teena et al., 2013). Threshold-based segmentation is a simple, fast and frequently used technique to divide image into component parts by thresholding method based on important characteristics such as constant reflectivity or light absorption. Edge-based segmentation divides image into different regions based on edge or gradient detection by using edge operators. Edge-based segmentation technique is not commonly used in the fields of fruit and vegetable quality detection due to the undefined edge of most fruits or vegetables (Teena et al., 2013). Region-based segmentation technique divides the image into component regions based on the similarity of pixels grouping together in brightness, color or texture. The segmented image divided by region-based segmentation technique can be represented as boundary or regions, which can be used to evaluate the size, shape, color, texture, and defects. Classification-based segmentation technique divides the image based on statistical methods. In the quality inspection of fruits and vegetables, classification-based segmentation technique has limited applications because of its sensitivity to the scale and rotation variations in a structural manner (Du & Sun, 2004).

Feature extraction is a technical term for methods of constructing combined variables to describe the image data with sufficient accuracy. Feature extraction is a crucial step that connects the image processing and analysis, and this technique transforms the image data, or segmented regions, into a set of features (feature vector). When the image segmentation is successfully performed, the external quality can be measured and described based on the relevant features extracted from the segmented areas. Therefore feature extraction is vital to the accuracy and precision of the external quality inspection. Generally, color features, shape features, texture features and size features of targets or segmented regions are always extracted for specific inspection task in the external quality detection.

5.2. Image analysis

Image analysis is a nondestructive method of computing measurements and statistics based on the interesting values of images' pixels, and their respective spatial location with the image. Image analysis operates on the features extracted from images and results in interpretations. Image analysis uses intuitive interpretation to display images and to mathematically manipulate images to help solve a computer vision problem without human being in loop. The results of image analysis can offer us insight to objects that it might contain, and allow us to perform measurements on those objects, or verification on their presence. Measurement and pattern classification are the most important parts of image analysis.

Measurement (or more accurately, vision measurement) is a method of quantitative analysis in the image analysis. Vision measurement refers to the process of measuring the interested parameters quantitatively based on the features extracted from the image. Different types of measurement can be made by using computer vision system. Typical measurements include the color, texture, and size. The measurements of color and texture can be obtained directly from pixels in the inspection images. However, for the size measurement obtained from the inspection image should be compared with the values that are specified in real-world unites. Therefore, calibration and verification are needed to convert the measurement from the digital image coordinate system to real-world coordinate system. In the external quality inspection of fruits and vegetables, some characteristics relative to the external quality, such as color, texture, areas, perimeters and lengths of the targets or segmented regions in the images, should be measured quantitatively. For example, the size can be evaluated by measuring the pixel number and perimeter of the segmented target area in the image, and the severity of the defects can be evaluated by measuring size and color of defect areas in the image.

Pattern classification, or pattern recognition, is a method of qualitative analysis in the image analysis. Pattern classification is the science of making inferences based on the measured features by using statistics, probability, multivariate analysis, computational geometry, and algorithm design techniques. As the classification methods described in the hyperspectral image processing and analysis section, the classification techniques can also be divided either supervised or unsupervised. The supervised methods are the most widely used in the image analysis. The objective of supervised learning methods is to construct models (classifiers) of the distribution of class labels in terms of corresponding features (Alfatni, Shariff, Abdullah, Ben Saeed, & Ceesay, 2011). Unsupervised classification methods classify the image mainly by seeking out similarity between selected features and using clustering algorithm without knowing any a priori knowledge of the class. The unsupervised classification methods are also found to be used in the image analysis of external quality inspection, but not as popular as the supervised one due to their uncertain classification results. The constructed classifiers are then used to assign class labels to testing samples (pixels, or segmented regions) where the sets of features are known, but the class label is unknown (Alfatni et al., 2011; Kotsiantis, Zaharakis, & Pintelas, 2006). Support vector machine (SVM), Adaptive Boosting (AdaBoost), k-Nearest Neighbor (k-NN), Artificial Neural Network (ANN), and decision tree are the widely used pattern classification methods in image processing and analysis in the food inspection industry. SVM is a supervised non-parametric statistical learning technique, which is widely used for classification by constructing a hyperplane or a set of hyperplanes in a high dimensional space. As SVM, AdaBoost is one of the most successful supervised classification methods with the aim to maximize the minimum margin of a training sample. Therefore, AdaBoost is widely used for classification in pattern recognition by constructing a 'strong' classifier with linear sets of simple 'weak' classifiers. k-NN is a non-parametric classification method cache of all the training data and predicts the response of the new sample by analyzing a certain number of the nearest neighbors in the feature space of the sample. ANN is a typical non-linear supervised classification method inspired by animals' central nervous system (brain). ANN uses mathematical models (functions), which simulate biological neural networks, to classify samples into different classes by finding common features between samples of known feature class. More details about pattern recognition and classification methods can be found in a review on learning techniques used in computer vision for food quality evaluation presented by Du and Sun (2006). In the external quality inspection of fruits and vegetables, pattern classification technique is frequently used to recognize the shape, types of defects, stems and calyxes from the segmented regions or targets in the image analysis step.

6. Applications of computer vision in the external quality inspection of fruits and vegetables

Computer vision systems, including the traditional, hyperspectral and multispectral computer vision systems, have been widely used in the fruit and vegetable industry for inspecting the external quality features and grading in terms of the appearance condition.

In the subsequent sections, we shall give a detailed summarization of the recent researches on computer vision for the external quality inspection of fruits and vegetables.

6.1. Applications of color inspection

Color is one of the most important sensorial quality attributes of fruits and vegetables, and it is the first factor that influences the consumer to choose or reject the fruits or vegetables. Color of fruits and vegetables is governed by the internal biochemical, microbial, physical and chemical changes which occur in growth, ripeness, and postharvest handling and processing stages, therefore color inspection has been used as the indirect measurement of some internal quality attributes, such as maturity, freshness, variety and desirability, and safety (Pathare, Opara, & Al-Said, 2013; Wu & Sun, 2013).Color is the most elementary information that is stored in pixels, and it contains the basic visual information in the images corresponding to human vision (Zheng, Sun, & Zheng, 2006). Due to the traditional color cameras imitate the human vision. Therefore color inspection is always conducted with traditional computer vision system.

The color of an object could be represented by several color spaces (color coordinate systems). In the color inspection of fruits and vegetables, RGB color space, HSI (hue, saturation and intensity) space, Hunter Lab space, Commission International de L'Eclairage (CIE) L*a*b* space, and CIE XYZ space are the most commonly used color spaces.

The images are acquired and stored in RGB color space in most computer vision systems, and each pixel in the images is composed of three integers which represent the intensity value of red, green and blue wavelengths. RGB color space is one of the most widely used color spaces in the color inspection tasks. V. Leemans graded Golden Delicious and 'Jonagold' apples into four categories according to European standards based on external quality by using a traditional computer vision system. In color grading, they used a simple neural network with no hidden layer to grade the apples by using RGB values (Leemans, Magein, & Destain, 2002). The overall accuracy of 78% was achieved. Kurita investigated the use of an index based on red and green component ratio (R/G) to grade the tomatoes according to their color (Kurita, 2006). They found that an index based on a red and green color component ratio could offer more reliable results than only using a single color component. This was probably due to the fact that a ratio between the two components could reduce the influence of the uneven distribution of the lightness in the different areas of the tomatoes. A study conducted by Blasco et al. investigated a computer vision-based sorting machine to detect and remove the unwanted materials and grade the pomegranate arils into four different quality classes by color based on R/G ratio and Bayesian Linear Discriminant Analysis (LDA) in the RGB color space (Blasco, Aleixos, Gomez-Sanchis, & Molto, 2009; Blasco, Cubero, Gomez-Sanchis, Mira, & Molto, 2009). An overall accuracy of 90% was achieved when using the combination of the red and green color component and the proposed algorithm.

However, the RGB color space is hardware-orientated space, or device-dependent space (different devices may produce different RGB values for the same pixel in the image). For this reason, several transformations have been made to standardize values, such as transform the RGB color space to standard RGB (sRGB) color space, or human-orientated spaces which are closer to the human perception of color, like HSI color space, or instrumental spaces which are uniform color spaces, like Hunter Lab space, CIE L*a*b* space, and CIE XYZ space (Cubero, Aleixos, Molto, Gomez-Sanchis, & Blasco, 2011). Zou et al. used both RGB and HIS color spaces to grade the Fuji apples into four different categories by color (Zou, Zhao, & Li, 2007). They found that the organization feature parameter (OFP) method was more accurate than back-propagation artificial neural network (BP-ANN), but a litter lower than support vector machine (SVM) for identification results. sRGB, HSV, and CIE L*a*b* color spaces were compared in their suitability for color quantification and measurement in curved surfaces of fruits and vegetables, and the results showed that the CIE L*a*b* color space was the best space for the color inspection in agricultural products with curve surfaces (Mendoza, Dejmek, & Aguilera, 2006). The Hunter's a/b ratio was used as an index in apple, citrus, tomato, and carambola fruit (Pathare et al., 2013; Little, 1975; Stewart & Wheaton, 1971). Kondo, Chong, Ninomiya, Ninomiya, and Monta (2005) developed an eggplant grading system to sort the eggplants according to surface defects and color by using NIR-color CCD camera, and the color analysis was conducted using both chromaticity conversion and HSI conversion methods. They found that the HIS color space was more intuitive and efficient in color evaluation compared to the other spaces. This was

Table 1
Summary of studies about the color inspection of fruits and vegetables.

Products	Species	Application	Color space	Accuracy	Reference
Fruits	Apple	Sorting by color and size	HSI	98%	
	Apple	Grading by color	RGB and HSI	–	Zou et al. (2007)
	Apple	Color classification	HSI	90%	Tao, Heinemann, Varghese, Morrow, and Sommer (1995)
	Apple	Grading by external quality	RGB	78%	Leemans et al. (2002)
	Apple	Maturity discrimination	RGB	95.83%	Garrido-Novell et al. (2012)
	Apple	Color classification	HSI	100%	Singh Chauhan and Partap Singh (2012)
	Citrus	Maturity evaluation	HSI	–	Yi-bin et al. (2006)
	Citrus	Quality evaluation	RGB	–	Kondo et al. (2000)
	Citrus	Color evaluation	RGB	$R^2 = 0.925$	Vidal et al. (2013)
	Citrus	Color evaluation	HSI	–	Chong, Kondo et al. (2008), Chong, Nishi et al. (2008)
	Mango	Sorting by external quality	HSI	–	Yimyam et al. (2005)
	Banana	Quality evaluation	RGB	–	Wang et al. (2009)
	Banana	Color measurement	sRGB, HSV, L*a*b*	97%	Mendoza et al. (2006)
	Banana	Color evaluation	CIE L*a*b*	–	Kang, East, and Trujillo (2008)
	Pomegranate	Grading by color	RGB	90%	Blasco, Aleixos et al. (2009), Blasco, Cuberoet al. (2009)
	Strawberry	Grading by external quality	CIE L*a*b*	88.8%	Liming and Yanchao (2010)
	Sweet cherry	Color rating	RGB	>85%	Wang, Li, Tollner, Gitaitis, and Rains (2012), Wang, Zhang, and Mujumdar (2012)
	Oil palm	Ripeness inspection	HSI	90%	Abdullah, Guan, Mohamed, and Noor (2002)
	Oil palm	Ripeness inspection	RGB	–	Alfatni et al. (2008)
	Carambola	Maturity discrimination	HSI	95.3%	Abdullah, Mohamad-Saleh, Fathinul-Syahir, and Mohd-Azemi (2006)
	Peach	Sorting by color and size	HSI	90%	Esehaghbeygi et al. (2010)
	Jatropha	Ripeness evaluation	RGB	–	Effendi, Ramli, Ghani, and Rahman (2009)
	Pear	Grading by external quality	HSI	–	Kondo (2010)
Vegetables	Tomato	Color classification	RGB	–	Lino et al. (2008)
	Tomato	Classifying by color and size	RGB	–	Louro, Mendonça, and Gonzaga (2006)
	Tomato	Ripeness & postharvest life assessing	CIE L*a*b*	–	López Camelo and Gómez (2004)
	Potato	Color classification	RGB	90%	Noordam et al. (2000)
	Potato	Blemish detection	RGB	89.6%	Barnes, Duckett, Cielniak, Stroud, and Harper (2010)
	Potato	Grading by color	HSI	90%	Tao et al. (1995)
	Mushroom	Disease inspection	CIE L*a*b*	–	Vízhányó and Felföldi (2000)
	Eggplant	Grading by external quality	HSI	–	Kondo et al. (2005)
	Pepper	Sorting by color and defects	HSI	96%	Shearer and Payne (1990)

probably due to that the HIS color space is human-orientated space and can provide similar color sensory with human evaluation. Table 1 shows a detailed summary of studies about the color inspection of fruits and vegetables.

6.2. Applications of texture inspection

As color attribute, texture is the other significant sensory quality attribute that has been frequently used in the external quality inspecting and grading systems for the agricultural product quality evaluation. Texture is closely related to some internal quality of fruits and vegetables, such as maturity and sugar content. Therefore texture is one of the widely used indicators the consumer used for quality assessment of fruits and vegetables. Texture analysis can also play an important role in defect recognition and segmentation in grading systems due to its powerful discriminating ability.

The aim of texture analysis is to try to discriminate different patterns in images by obtaining the variance of intensity values across pixels or by extracting the dependency of intensity values between pixels and their neighboring pixels (Haralick, 1973; Kartikeyan & Sarkar, 1991). There are four different types of texture, i.e. statistical texture, model-based texture, structural texture, and transform-based texture (Zheng et al., 2006). Statistical texture, including gray level co-occurrence matrix, gray level pixel-run length matrix and neighboring gray level dependence matrix, can be extracted by using statistical methods on a matrix which is obtained based on the orders of the intensity values of pixels across images (Bharati, Liu, & MacGregor, 2004). Model-based texture including random field model, fractal model, and autoregressive model texture, can be extracted by calculating coefficients from a fractal or autoregressive model according to the relationship of the intensity values between pixels and their neighboring pixels (Zheng et al., 2006). Structural texture refers to statistical distributions of some structural primitives such as lines, edges, or bumps that constructed by intensity values of pixels. Transform-based texture, including convolution mask, Fourier transform, and Wavelet transform based texture, can be extracted by using statistical methods in corresponding spatial frequency domain images. Among them, the statistical texture is the most commonly used one in the texture analysis and evaluation of fruits and vegetables for its high accuracy and low computational cost. Model-based texture and transform-based texture are also found to be used in the food external quality inspection industry. Structural texture is rarely used in agricultural products due to the texture in the food is too various and irregular to be described by some structural primitives.

Statistical texture is usually used to analyze the smoothness, graininess, and coarseness of products (Du & Sun, 2004). The statistical texture of fruits and vegetables between sound and defect skin, or during different maturity stages, even for different sugar, acidity, or starch contents, might be very different. Statistical texture can therefore be used to inspect the external or internal quality of fruits and vegetables. Mendoza and Aguilera developed a computer vision system to identify the ripening stage of bananas according to the color, brown spots, and statistical texture information based on co-occurrence matrix (Mendoza & Aguilera, 2004). They found that it was possible to classify 49 banana samples in their 7 ripening stages with an accuracy of 98%. The results indicate that the proposed method is robust on-line discriminating the ripening stages of bananas. Hu et al. developed a traditional computer vision system to recognize the banana hand and finger at various ripening stages by using a novel two-step k-means clustering algorithm. The flaws on the banana surface were successfully segmented by the second k-mean clustering step. Kondo et al. believed the color, size, shape and surface texture could reflect the sweetness of oranges to some extent. They developed a traditional computer vision system by using a color TV camera to evaluate the sugar content and acid content of Iyokan orange fruits. Several neural networks were used and a reasonable accuracy result was achieved (Kondo, Ahmad, Monta, & Murase, 2000). Kim et al. used the color co-occurrence method to inspect the grapefruit peel diseases (Kim, Burks, Qin, & Bulanon, 2009). It was found that grapefruit peel diseases were differentiated from sound ones with classification accuracy as high as 96.7%. The results indicate that traditional computer vision system and texture feature analysis could be used for classifying the grapefruit peel diseases. A similar approach was described by Zhao et al. to detect the citrus peel disease in HIS color space (Zhao, Burks, Qin, & Ritenour, 2009). The best overall classification accuracy of 95% was achieved by using the HIS model and proposed algorithm. The results indicate that co-occurrence matrix features are effective in differentiating citrus peel conditions. Applications by applying statistical texture especially co-occurrence matrix method can be found in ripeness evaluation of strawberries and apples (ElMasry, Wang, ElSayed, & Ngadi, 2007; Letal, Jirak, Suderlova, & Hajek, 2003), starch content assessment of apples (Menesatti et al., 2009), defect inspection of apples (Kavdir & Guyer, 2002), and texture grading of pears (Zhang & Wu, 2012). Model-based texture and transform-based texture are also used in the quality inspection task, but not as popular as the statistical texture. Zhu et al. introduced a method to inspect the apple quality with the Wavelet transform based texture (Zhu, Pan, & McHugh, 2007). Another example of such work was presented by Quevedo et al., who monitored the ripening process of bananas with fractal texture by analyzing the "senescence spotting" of the banana peel (Quevedo, Mendoza, Aguilera, Chanona, & Gutierrez-Lopez, 2008). The results show that transform-based texture features are more effective in some situations.

6.3. Applications of size inspection

The size is a particular important aspect of external appearance of fruits and vegetables, the price of agricultural products is usually related with their size, therefore grading of fruits and vegetables into different size groups is always necessary in the postharvest handling and processing stages. Size inspection can be conducted with traditional computer vision system, or multispectral computer vision system with a filter centered on NIR wavelengths.

Inspection of the size of spherical or quasi-spherical objects is relatively easy, but it becomes more and more complex to the fruits and vegetables due to their natural irregularities (Cubero et al., 2011). Projected area, perimeter, length and width are three most commonly used features to measure the size of fruits and vegetables in the preview studies for external quality evaluation (Du & Sun, 2004). Since the digital images captured by the computer vision systems are composed of pixels, the projected area, perimeter, or length and width features can be measured in the images by using image processing algorithms. The most commonly used and basic convenient measurement for size evaluation is the projected area. And it can be acquired by counting the pixels within the area straightforwardly. Perimeter feature can be extracted by summing the distance between every two neighboring pixels on the boundary of inspected products (Zheng et al., 2006). The length and width of an object from a segmented image can also be found to be used to measure the size of fruits and vegetables in previous researches. However, due to the irregular shape of agricultural products and the orientation of the products with respect to the camera, the measurement of length and width parameter is not as easy as that of the projected area and perimeter. In addition to the above size parameters, radius, equatorial diameter, and major and minor axes are some other features which are also used in the food quality inspection industry.

A computer vision based on date grading and sorting systems was developed by Al Ohali to classify the dates into three categories according to their size and shape (Al Ohali, 2011). From the segmented image, the size is estimated by calculating the area covered by the fruit in the segmented image. The classification results show that the proposed system can sort 80% dates accurately. However, in their study, grades were based on human perception, and the classification accuracy might not be objective. Similar methods to inspect the size based on projected area were used to sort strawberries, potatoes, tomatoes, mangos (Bato, Nagata, QiXin, Hiyoshi, & Kitahara, 2000; Hasankhani & Navid, 2012; Jahns, Møller Nielsen, & Paul, 2001; Noordam, Otten, Timmermans, & van Zwol, 2000; Yimyam & Clark, 2012). Throop, Aneshansley, Anger, and Peterson (2005), Esehaghbeygi, Ardforoushan, Monajemi, and Masoumi (2010) and Hahn (2002) investigated the use of the characteristics of length and width for measuring the size of apples, peaches and chilies respectively. Diameter (or equatorial diameter, radius) is also an indicator of size. Some image processing based systems were developed by Aleixos et al. (2002), Khojastehnazhand, Omid, and Tabatabaeefar (2010), Liming and Yanchao (2010), and Zou and Zhao (2009) to sort the citrus, strawberries, and apples respectively according to their diameters. The classification results of the researches above are barely satisfactory. However, one single size feature might not be sufficient to determine the size of fruits or vegetables in some case, and many previous studies combined two or several size features to evaluate the size attribute. A grading robot system was developed by Kondo (2009) to inspect all sides of fruits. In his system, Heywood Diameter, maximum length, breadth, and Feret's diameters were used for fruit size measurement. The results showed that the grading system was very successful in automation due to the combination of these size features offering a more reliable and comprehensive classification. Combined size features can also be found in the applications of sorting of apples (combined area and the principal axis of inertia, Blasco, Aleixos, & Molto, 2003), tomatoes (combined largest diameter, the major axis and area, Jahns et al., 2001), dates (combined length and area by using reflective near-infrared imaging, Lee, Schoenberger, Archibald, & McCollum, 2008; Lee, Kang, Delwiche, Kim, & Noh, 2008), papayas (combined area, mean diameter, and perimeter, Riyadi, Rahni, Mustafa, & Hussain, 2007), lemons (combined area and equatorial diameter, Lino, Sanches, & Dal Fabbro, 2008), and eggplants (combined area and equivalent diameter, Kondo et al., 2007; combined diameter and length, Chong, Kondo, Ninomiya, Nishi, Monta, Namba et al., 2008a; Chong, Nishi, Kondo, Ninomiya, Monta, Namba et al., 2008b).

6.4. Applications of shape inspection

Shape is another important appearance attribute that affects the decision of customers on purchasing (Leemans & Destain, 2004). Agricultural products are expected to have a particular shape, fruits or vegetables with deformations or irregular shapes usually have lower prices, or even cannot be sold (Cubero et al., 2011). Therefore the shape of fruits and vegetables is one of the most important factors that should be taken into account for their quality classification and grading.

The shape is evaluated by the measurement of different features according to the different shapes of fruits and vegetables. Shape is easily comprehended by humans but very difficult to quantify or define by computer (Alfatni et al., 2011). Computer vision systems offer a solution for its measurement and inspection. The shape features can be extracted from digital images to characterize the shape of fruits and vegetables in order to discriminate the different shapes during processing, or to estimate the acceptance or rejection of product shape for customers (Du & Sun, 2004; Leemans & Destain, 2004; Zheng et al., 2006). Various features for shape description and measurement have been studied. Size-dependent features (including compactness, convexity, elongation, roundness, length, width, length/width ratio, etc.), boundary encoding, invariant moments, and Fourier descriptors are the most popular shape features applied in the quality inspection of food industry.

Size-dependent shape measurements use one single size parameter or combine two or more different size parameters to form dimensionless expressions for shape description (Zheng et al., 2006). Size-dependent shape measurements are relatively coarse methods, and the size-dependent features can only reflect the overall shape of the objects. The earliest class of shape descriptors is simply based on size parameters (Du & Sun, 2004). Due to its easy realization and less time-consuming, in some works, the size-dependent shape features are still widely used for the overall shape sorting of apples, citrus, peaches, potatoes, eggplants, etc. (Sadrnia, Rajabipour, Jafary, Javadi, & Mostofi, 2007; Kondo et al., 2000; Zhang, Spadaro, Garibaldi, & Gullino, 2010; Jahns et al., 2001; Kondo et al., 2007). The shape classification accuracies of the above researches indicate that size-dependent features are efficient for the shape classifying the products with regular shapes.

However, for some species of fruits and vegetables with very irregular shapes, only using the size-dependent features is not sufficient to determine their shapes. Boundary encoding, invariant moments, and Fourier descriptors are three more powerful size-independent features for shape descriptions and measurements independent of size measurements. Boundary encoding describes the shape by using a chain code vector which records the sequence of coordinates of pixels on the boundary. Invariant moments describe the shape by their magnitudes which are invariant under translation, rotation, and also changes in scale. Fourier descriptors describe the shape by taking the Fourier transform of the boundary of the two-dimensional object in the image. To characterize the shapes of products more accuracy, the size-independent features are widely used for the shape inspection of apples, cherries, citrus, potatoes etc. (Beyer, Hahn, Peschel, Harz, & Knoche, 2002; Currie, 2000; Noordam et al., 2000). Shape features extracted by using boundary encoding, invariant moments and Fourier descriptors are abstract and in comprehensible for us, however, the classification results of the above researches show that the size-independent features are more accurate and reliable for irregular product classification compared to the size-dependent features.

Actually, using one single type of shape feature is always not sufficient to determine the shape, in order to get a more accurate shape classification result, in most applications, more than one shape features are used to sort the fruits or vegetables (Brewer et al., 2006; Jahns et al., 2001; Kondo, 2009; Zhang & Wu, 2012). The results show that a combination of two or more shape features offers more reliable and sophisticated shape classification. To make the shape easier to define, backlighting is used to obtain high contrast images in some applications whose task is just to discriminate the shape of products (Costa et al., 2009). Table 2 shows a detailed summary of studies about the shape inspection of fruits and vegetables.

6.5. Applications of surface defect inspection

The presence of surface defects influences the quality and price of fruits and vegetables, and early weeding out of the fruits and vegetables with serious defects can prevent the infection of the whole patch. Therefore detection of surface defects is the most commonly extended application of image and spectral analysis to the external quality inspection of fruits and vegetables.

Visual inspection of fruits and vegetables with respect to color, texture, size, and shape by traditional computer vision is already automated in the commercial sorting machines. However, sorting by defects is still a challenging task due to the high variance of defect types and existence of stem/calyx concavities (Unay & Gosselin, 2006). The color, texture, or internal components of defects may be different from that of the sound, therefore color, texture, or spectral reflectance is usually selected as the defect features to discriminate the defects from the sound peel. Many applications aimed to detect defects based on these features have been described by using traditional computer vision system, hyperspectral or multispectral computer vision system.

For traditional computer vision system, it is relatively easy to detect some types of defects that present darker lightness or obvious texture character in the images of fruits and vegetables. In order to avoid previous training given by experts when classifying each pixel to sound or defect class, Blasco, Aleixos, and Molto (2007) developed a region oriented segmentation algorithm to detect the peel defects of citrus in HIS color space with an accuracy of 95% by using traditional

Table 2
Summary of studies about the shape inspection of fruits and vegetables.

Products	Species	Application	Shape features	Accuracy	Reference
Fruits	Apple	Shape grading	Fourier descriptors	–	Xiaobo et al. (2008)
	Apple	Evaluating apple shape	Fourier descriptors	–	Currie (2000)
	Apple	Characterizing apple shape	Fourier descriptors	–	Paulus and Schrevens (1999)
	Pear	Grading by external quality	Eight size-dependent shape features	88.2%	Zhang and Wu (2012)
	Pear	Grading by external quality	Roundness, complexity, deformativity	–	Kondo (2009)
	Pear	Shape identification	Fourier descriptors	90%	Ying, Jing, Tao, and Zhang (2003)
	Citrus	Inspection and classification	Maximum and minimum diameters	>94%	Aleixos et al. (2002)
	Citrus	Quantitative evaluation of shape	Fourier descriptors	–	Costa et al. (2009)
	Kiwifruit	Shape classification	Length to major diameter ratio and major diameter to minor diameter	–	Rashidi, Seyfi, and Gholami (2008)
	Strawberry	Grading by size and shape	?	98.6%	Bato et al. (2000)
	Strawberry	Grading by external quality	Features based on sharing line method	90%	Liming and Yanchao (2010)
	Cherry	Shape analyzing	Boundary encoding	$R = 0.99$	Beyer et al. (2002)
	Star fruit	Shape discrimination	Fourier descriptors	100%	Abdullah et al. (2006)
	Date	Date grading by external quality	Fourier descriptors	80%	Al Ohali (2011)
	Mango	Physical properties analysis	Length and width	–	Yimyam et al. (2005)
	Mango	Mango grading	Fourier descriptors	89.83%	Khoje and Bodhe (2012)
	Papaya	Shape classification	Wavelet-based features	98%	Riyadi et al. (2007)
	Watermelon	Shape classification and analysis	Length to width ratio and fruit area to background area ratio	–	Sadrnia et al. (2007)
Vegetables	Tomato	Shape grading	Fourier based separation technique	89%	Tao et al. (1995)
	Tomato	Quality grading	Compactness and eccentricity	–	Jahns et al. (2001)
	Tomato	Shape variation analysis	Ratio of maximum height to width, ratio of midheight to midwidth	–	Brewer et al. (2006)
	Tomato	Irregularity evaluation	Width to length ratio	–	Morimoto et al. (2000)
	Potato	Quality inspection and grading	Fourier descriptors	>97.6%	Noordam et al. (2000)
	Potato	Sorting of irregular potatoes	Roundness, extent, and Fourier descriptors	100%	ElMasry, Cubero et al. (2012), Elmasry, Kamruzzaman et al. (2012)
	Potato	Grading by size and shape	Fourier descriptors	97%	Heinemann, Pathare, and Morrow (1996)
	Potato	Irregularity evaluation	Fourier descriptors	98.1%	Zhang et al. (2014b)
	Eggplant	Quality grading	Difference between maximum and minimum diameters	–	Chong, Kondo et al. (2008), Chong, Nishi et al. (2008)
	Pepper	Volume estimation	Length to diameter ratio	–	Ngouajio, Kirk, and Goldy (2003)

computer vision system. Hu, Dong, Liu, and Malakar (2014) developed a novel two-step k-means clustering technique to segment the banana hand and banana finger at various ripening stages in RGB color space by using traditional computer vision system. The potential of the algorithm was proved by the satisfactory results. To detect the peel condition of whole surface, Zou, Zhao, Li, and Holmes (2010) developed a computer vision system with three color cameras to acquire the total surface of fruits and vegetables. Good separation between sound and defective apples was achieved by using their proposed system. However, it was found that defective apples were differentiated from the sound ones just according to the fact that two or more region of interest (ROIs) would be extracted from the defective apples because the calyx and stem could not appear in one image. The disadvantage of their method is that it could not distinguish the true defects and calyx/stem-end. One concern for image acquisition of spherical and curved fruits and vegetables is that lighting reflectance is not uniformly distributed (Li, Huang, Zhao, & Zhang, 2013; Li, Rao, Wang, Wu, & Ying, 2013; Tao, 1996). Li, Rao et al. (2013) and Li, Huang et al. (2013) developed a traditional computer vision system to detect the common defects on oranges by using combined lighting transform and image ratio methods. The result with 98.9% overall detection rate was obtained by using their proposed system and algorithm. Their algorithm is effective in differentiating normal and defective oranges. However, the disadvantage is that it could not distinguish between different types of defects.

However, lack of spectral information in conventional color images, traditional computer vision system is not efficient for the inspection of some defects with similar color and texture as sound peel, such as bruises, rottenness, or chilling injury. Hyperspectral and multispectral computer vision systems provide powerful tools not only to detect skin defects but also to differentiate between a variety of defects that have similar color and texture or even to detect some defects that are not clearly visible (Lorente et al., 2012). Bruising is one of the familiar defects occurring on fruits and vegetables during postharvest handling and processing stages. The existing commercial sorting machines are still not available in detecting bruises (Baranowski, Mazurek, Wozniak, & Majewska, 2012; Xing, Saeys, & De Baerdemaeker, 2007). An experiment using a hyperspectral computer vision system for bruise detection on apples was conducted by Xing et al. (2007). PCA and PLSDA were used to extract the spectral and spatial features from the hyperspectral images in the region between 400 and 1000 nm. Their experiment proved that combination of image processing and chemometric tools had a potential in detecting the bruises on apples. Chilling injury is a common defect occurring during storage and transportation at low temperatures. Liu, Chen, Wang, Chan, and Kim (2006) developed a hyperspectral computer vision system to acquire visible/near-infrared (NIR) image in 700–850 nm to detect the chilling injury in cucumber by using band ratio and PCA methods. Results revealed that either band ratio algorithm ($Q_{811/756}$) or PCA transform in a spectral region between 733 and 848 nm could detect the chilling injury with an accuracy of over 90%. The results indicate that chilling injury is relatively difficult to inspect at the initial post-chilling room temperature stage due to insignificant manifestation of chilling induced symptoms during

Table 3
Summary of studies about the defect detection of fruits and vegetables.

Products	Species	Applications	Types of CVS	Methods	Accuracy	Reference
Fruits	Apple	Grading by defects	T-CVS	K-means	73%	Leemans and Destain (2004)
	Apple	Defect detection	T-CVS	Three color cameras	89%	Zou et al. (2010)
	Apple	Quality grading	M-CVS	Statistical and syntactical classifiers	93.5%	Unay et al. (2011)
	Apple	Defect segmentation	M-CVS	ANN	–	Unay and Gosselin (2006)
	Apple	Quality evaluation	M-CVS	Flat-field correction	95%	Throop et al. (2005)
	Apple	Grading by external quality	T-CVS	Gaussian and non-parametric model	78%	Leemans et al. (2002)
	Apple	Bruise detection	H-CVS	PCA, MNF, SIMCA, LDA, SVM	–	Baranowski et al. (2012)
	Apple	Defect detection	H-CVS	ASD	–	Mehl, Chen, Kim, and Chan (2004)
	Apple	Defect and feces detection	M-CVS	_	–	Kim, Cho, Lefcourt, Chen, and Kang (2008)
	Apple	Bruise detection	H-CVS	PLS, SDA	93.95%	ElMasry et al. (2008)
	Apple	Efficient wavelength selection	M-CVS	QDA	–	Kleynen, Leemans, and Destain (2003)
	Apple	Rottenness detection	H-CVS	LDA, CART	91.2%	Gomez-Sanchis, Gomez-Chova et al. (2008), Gomez-Sanchis, Molto et al. (2008)
	Apple	Bitter pit detection	H-CVS	PLS	–	Nicolai, Lotze, Peirs, Scheerlinck, and Theron (2006)
	Apple	Defect detection	M-CVS	ANN	95.4%	Ariana, Guyer, and Shrestha, (2006), Ariana, Lu, and Guyer (2006)
	Apple	Defect detection	H-CVS	BR	99.5%	Kim et al. (2007)
	Apple	Defect detection	H-CVS	SD, PCA	–	Mehl et al. (2004)
	Apple	Decayed spot, wound and rot detection	M-CVS	BR	92.42%	Lee, Schoenberger, Archibald and McCollum (2008), Lee, Kang, Delwiche, Kim and Noh (2008)
	Apple	Bruise detection	H-CVS	PCA, PLSDA	86%	Xing et al. (2007)
	Apple	Bruise detection	M-CVS	PCA, MT	86%	Xing et al. (2005)
	Apple	Bruise detection	H-CVS	PCA	>77.5%	Xing et al. (2005)
	Apple	Bruise detection	H-CVS	PCA, MNT	88%, 94%	Lu (2003)
	Apple	Defect detection	M-CVS	Rotating	90%	Bennedsen, Peterson, and Tabb (2005)
	Apple	Defect detection	M-CVS	PCA, ANN	79%	Bennedsen, Peterson, and Tabb (2007)
	Apple	Chilling injury detection	H-CVS	ANN	98.4%	ElMasry et al. (2009)
	Apple	Bruise detection	H-CVS	MNF	97.1%	Zhang et al. (2014a)
	Citrus	Canker detection	M-CVS	BR, T	95.3%	Qin, Burks, Zhao, Niphadkar, and Ritenour (2012)
	Citrus	Skin damage detection	M-CVS	Bayesian discriminant analysis	86%	Blasco, Aleixos, Gomez-Sanchis and Molto (2009), Blasco, Cubero, Gomez-Sanchis, Mira and Molto (2009)
	Citrus	Peel defect detection	T-CVS	Region oriented segmentation	95%	Blasco et al. (2007)
	Citrus	Common defect detection	T-CVS	Lighting transform and image ratio	98.9%	Li, Huang, Zhao and Zhang (2013), Li, Rao, Wang, Wu and Ying (2013)
	Citrus	Common defect detection	H-CVS	PCA	93.7%	Li et al. (2011)
	Citrus	Light correction	H-CVS	Light correction	–	Gomez-Sanchis, Gomez-Chova et al. (2008), Gomez-Sanchis, Molto et al. (2008)
	Citrus	Fly infestation detection	H-CVS	Particle analysis	–	Haff et al. (2013)
	Citrus	Rottenness detection	H-CVS	ANN, DT	98%	Gomez-Sanchis et al. (2012)
	Pear	Bruise detection	H-CVS	PCA, MLC, EDC, MDC, SAM	93.8–95%	Zhao, Ouyang, Chen, and Wang (2010)
	Banana	Hand and finger segmentation	T-CVS	Two-step k-means	–	Hu et al. (2014)
	Strawberry	Bruise detection	H-CVS	LDA, ND, ANN	100%	Nagata, Tallada, and Kobayashi (2006)
	Cherry	Pit detection	H-CVS	NN	97%	Qin and Lu (2005)
	Olive	Quality classification	T-CVS	NN, PLS, MD	70–90%	Diaz et al. (2004)
	Jujube	Insect infestation detection	H-CVS	JMP, MA	97%	Wang et al. (2011)
Vegetables	Potato	Quality inspection	T-CVS	SVM, KNN, MLPs	–	Razmjooy et al. (2012)
	Cucumber	Bruise detection	H-CVS	PCA, BR	75–95%	Ariana, Guyer et al. (2006), Ariana, Lu et al. (2006)
	Cucumber	Chilling injury detection	H-CVS	PCA, FLD	91%	Cheng et al. (2004)
	Cucumber	Chilling injury detection	H-CVS	BR, PCA	>90%	Liu, Chen, Wang, Chan, and Kim (2005), Liu et al. (2006)
	Cucumber	Fly infestation detection	H-CVS	PLS	88–93%	Lu and Ariana (2013)
	Mushroom	Bruise detection	H-CVS	PCA	79–100%	Gowen et al. (2008)
	Mushroom	Freeze damage detection	H-CVS	PCA, LDA	95%	Gowen, Taghizadeh, and O'Donnell (2009)
	Mushroom	Enzymatic browning	H-CVS	PLS-DA	–	Taghizadeh, Gowen, and O'Donnell (2011)
	Onion	Sour skin disease detection	H-CVS	MS	–	Wang et al. (2009)

T-CVS: traditional computer vision system; H-CVS: hyperspectral computer vision system; M-CVS: multispectral computer vision system; BR: band ratio; MS: mean reflectance spectra; ASD: asymmetric second difference; MT: moment thresholding; T: thresholding.

the first 0–2 days in storage. However, the acquisition and processing of the hyperspectral images are time-consuming, the redundancy data makes the hyperspectral computer vision system impossible to be used in-line or real-time. Actually, the hyperspectral imaging is always used for analysis and determining the effective wavelengths for a multispectral computer vision system. Based on hyperspectral images and PCA, four efficient wavelengths (558, 678, 728, and 892 nm) were selected, and then a multispectral computer vision system was developed by Xing et al. (2005) to detect the bruises on apples. The Principle Component Analysis (PCA) on the multi-spectral images offers very similar results as PCA results on the hyperspectral images. An overall accuracy of about 86% was obtained with their system and algorithms. Their research lays a foundation for the development of multispectral computer vision system for on-line or real-time bruise detection on

'Golden Delicious' apples. Table 3 shows a detailed summary of studies about the defect detection of fruits and vegetables by using different computer vision systems.

7. Challenges and future trends

Computer vision systems have become a common and scientific tool in industrial and agricultural manufacturing automation due to superior performance, ongoing improvements in cost, ease of use, and algorithmic robustness (Teena et al., 2013). Three different types of computer vision systems, including traditional, multispectral, and hyperspectral computer vision systems, are currently widely used in the food industry for the external quality inspection of fruits and vegetables.

Traditional computer vision system is a powerful tool for the inspection of color, texture, size, shape, and some relatively obvious defects, but has less effectivity in detecting defects that are not clearly visible. To strengthen the traditional computer vision system, hyperspectral and multispectral computer vision systems provide powerful tools to detect some defects that are impossible or difficult to detect with traditional computer vision system due to the superiority of spectral images.

However, to realize the defect detection more rapidly and accurately in-line, there are still many challenges to be overcome. The challenges include stem–calyx recognition, the uneven distribution of lightness on curvature surface, whole surface inspection, long time consuming of acquisition and processing for spectral image, efficient wavelengths selection for different application, and different defects discrimination, etc.

Also, major advances in 3D techniques, Terahertz imaging, X-ray, and Raman imaging can be expected to be used in the quality inspection of fruits and vegetables.

8. Conclusion

Appearance characters, including color, texture, size, shape, and variety of defects, are the most important external sensory quality attributes of fruits and vegetables. Computer vision systems, including traditional computer vision system, hyperspectral computer vision system, and multispectral computer vision system, have been widely used in the quality inspection of food and agricultural products to replace manual inspection as they can provide a rapid, accurate, objective and non-destructive assessment. Many successful applications have proved that the computer vision systems are scientific and powerful tools for the accurate and rapid automatic external quality inspection of fruits and vegetables. This paper reviews the principles, developments and applications of three different computer vision systems in the external quality inspection of fruits and vegetables. In spite of that there are still many challenges to be overcome, as a promising technology, computer vision will continuously play an indispensable role in the researches and applications for quality inspection of fruits and vegetables.

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