Review

Hyperspectral and multispectral imaging for evaluating food safety and quality

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Abstract

Spectral imaging technologies have been developed rapidly during the past decade. This paper presents hyperspectral and multispectral imaging technologies in the area of food safety and quality evaluation, with an introduction, demonstration, and summarization of current spectral imaging techniques available to the food industry for practical commercial use. The main topics include methods for acquiring spectral images, components for building spectral imaging systems, methods for calibrating spectral imaging systems, and techniques for analyzing spectral images. The applications for evaluating food and agricultural products are presented to reflect common practices of the spectral imaging techniques. Future development of hyperspectral and multispectral imaging is also discussed.

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1. Introduction

Traditional optical sensing techniques, such as imaging and spectroscopy, have limitations to acquire adequate spatial and spectral information for nondestructive evaluation of food and agricultural products. Generally, conventional imaging cannot acquire spectral information and spectroscopy measurement cannot cover large sample areas. In recent years, spectral imaging (i.e., hyperspectral and multispectral) has emerged as a better tool for safety and quality inspection of various agricultural commodities. Spectral imaging technique combines conventional imaging and spectroscopy techniques, and it is able to obtain both spatial and spectral information from the target, which is extremely useful for evaluating individual food items. The technique has drawn tremendous interest from both academic and industrial areas, and has been developed rapidly during the past decade (Gowen et al., 2007; Sun, 2010; Lorente et al., 2012).

This review focuses on hyperspectral and multispectral imaging technologies in the field of food safety and quality evaluation. There is an introduction of spectral image acquisition methods in Section 2, with basic concepts and ground rules for the rest of the paper. The emphasis of the review is put on the introduction, demonstration, and summarization of spectral imaging techniques for practical uses, including essential components for building spectral imaging system (Section 3), methods for calibrating spectral imaging system (Section 4), and techniques for analyzing spectral images (Section 5). Applications of hyperspectral and multispectral imaging for food and agricultural products are reviewed in Section 6. Conclusions are presented in Section 7 by summarizing the paper and addressing future development.

2. Spectral image acquisition methods

Spectral images are three-dimensional (3-D) in nature, with two spatial dimensions and one spectral dimension. Based on the continuity of the data stored in the wavelength domain, spectral imaging can be divided into two main techniques: hyperspectral imaging and multispectral imaging. The hyperspectral technique acquires images with numerous (tens or hundreds) continuous wavebands, while the multispectral technique acquires images with a few (generally less than 10) discrete wavebands. A full spectrum can be extracted from each pixel in hyperspectral images. Multispectral images produce a set of isolated data points for each pixel due to the separate wavebands stored in the dataset.

2.1. Hyperspectral imaging

Hyperspectral imaging is often used to collect images with high spatial and spectral resolutions for fundamental research. The process usually involves a significant amount of time for image acquisition under laboratory conditions and relatively complicated procedures for offline image analysis. Generally, there are three approaches for acquiring 3-D hyperspectral cubes [hypercubes (x, y, z)]. These are point-scan, line-scan, and area-scan methods, as illustrated in Fig. 1. In the point-scan method (i.e., the whiskbroom method), a single point is scanned along two spatial dimensions (x and y) by moving either the sample or the detector. A spectrophotometer equipped with a point detector is used to acquire a single spectrum for each pixel in the scene. Hyperspectral image data are accumulated pixel by pixel. Two-axis motorized positioning tables are usually needed to move the sample or the detector to finish the scan of a complete scene.

The line-scan method (i.e., the pushbroom method) is an extension of the point-scan method. Instead of scanning one point each time, this method simultaneously acquires a slit of spatial information as well as full spectral information for each spatial point in the linear field of view (FOV). A special 2-D image (y, z), with one spatial dimension (y) and one spectral dimension (z), is taken at a time. A complete hypercube is obtained as the slit is scanned in the direction of motion (x). Hyperspectral systems using imaging spectrographs work in the line-scan mode.

On the one hand, both point-scan and line-scan methods are spatial-scan methods. The area-scan method (i.e., the band sequential method), on the other hand, is a spectral-scan method. This approach acquires a 2-D single-band grayscale image (x, y) with full spatial information at once. A hypercube containing a stack of single-band images is built up as the scan is performed in the spectral domain. No relative movement between the sample and the detector is required for this method. Imaging systems using filters (e.g., filter wheels and electronically tunable filters) operate by the area-scan method.

The point-scan method is a basic spectroscopic approach, using a light source that cannot cover a large area of the sample surface.
(e.g., point laser). Generally it is not practicable for fast image acquisition since the scan of many points for two spatial dimensions is time consuming. The line-scan method can acquire images from moving samples. Food commodities normally are moved linearly along a production line. Thus the line-scan method is well suited for online inspection of individual food items or continuous streams of bulk ingredients. When sample movement is undesirable, the area-scan method is usually used to collect images from the fixed scene.

2.2. Multispectral imaging

Multispectral imaging aims to acquire spatial and spectral information that are directly useful for real-time applications in the field (e.g., fruit packinghouses and food processing plants). The process generally involves fast image acquisition and simple algorithms for image processing and decision making. Reducing the total volume of the data is the key for building effective multispectral imaging systems. In practice, this means acquiring images with relatively low spatial resolutions at a few important wavelengths. Hyperspectral images are usually used as fundamental datasets from which to determine optimal wavebands that can be used by a multispectral imaging solution for a particular application.

In practical terms, the aforementioned point-scan method is not feasible for fast image acquisition because of its time-consuming scan along two spatial dimensions. The other two methods (i.e., line-scan and area-scan), however, can be adjusted to satisfy the requirements of rapid multispectral image acquisition. As illustrated in Fig. 2, both line-scan and area-scan methods can be implemented to collect images at fewer wavelengths than what would be used for hyperspectral imaging. For the line-scan method, this can be achieved by specifying the positions of all the useful tracks along the spectral dimension of the CCD detector. Only the data from the selected tracks are acquired, which reduces the amount of the data for each line-scan image \( y, \lambda \) and consequently shortens the acquisition time. The bandwidth of the selected tracks can be adjusted through pixel binning along the spectral dimension.

In contrast to the line-scan method, the area-scan method for multispectral imaging can simultaneously collect single-band images at multiple selected wavelengths. Light from the spatial scene is usually divided into several parts by optical separation devices (e.g., beamsplitter). The spectrally divided scenes will go through preset bandpass filters separately. Narrowband lights are commonly used as the excitation sources. When excited by high-intensity monochromatic light, some biological materials emit low-intensity light in a broad wavelength range. The energy change can cause fluorescence emission and/or Raman scattering, which carries information of the target that can be used for various inspection purposes.

3. Construction of spectral imaging systems

A spectral imaging system generally consists of a light source, a wavelength dispersive device, and an area detector. The components for building spectral imaging systems are presented in the following sections.

3.1. Light sources

Light sources for spectral imaging applications can generally be classified into two categories: illumination and excitation sources. Broadband lights are generally used as the illumination sources for reflectance and transmittance imaging. The spectral constitution of the incident light is not changed after light-sample interactions. The measurement is performed based on the intensity changes at different wavelengths. Narrowband lights are commonly used as the excitation sources. When excited by high-intensity monochromatic light, some biological materials emit low-intensity light in a broad wavelength range. The energy change can cause fluorescence emission and/or Raman scattering, which carries information of the target that can be used for various inspection purposes.

3.1.1. Illumination sources

Halogen lights are the most common broadband illumination source. Quartz tungsten halogen (QTH) lamps generate a smooth spectrum in the visible to infrared wavelength range. QTH lamps can be used to directly illuminate the target or be placed in a lamp housing from which the light is delivered to the target via an optical fiber. Halogen sources have been intensively used in applications of hyperspectral/multispectral reflectance measurements for food surface inspection (Kim et al., 2001; Park et al., 2002; Lu, 2003). High-intensity QTH lights have also been used in transmittance measurements for detecting internal attributes or constituents within agricultural commodities (Qin and Lu, 2005; Ariana and Lu, 2008; Yoon et al., 2008). Besides the halogen sources, broadband light-emitting diodes (LEDs) have started to find applications for food safety and quality inspection (Lawrence et al., 2007; Chao et al., 2008), owing to their advantages over traditional lighting, such as long lifetime, low power consumption, low heat generation, small size, fast response, robustness, and non-sensitivity to vibration.

3.1.2. Excitation sources

Lasers are powerful monochromatic sources widely used for excitation purposes. Light from lasers is generated through stimu-
lated emission, which usually occurs inside a resonant optical cavity filled with a gain medium (e.g., gas, dye solution, semiconductor, and crystal). They can operate in CW (continuous wave) mode or pulse mode in terms of temporal continuity of the output. Lasers are the ideal excitation sources for fluorescence and Raman measurements owing to their highly concentrated energy, perfect directionality, and true monochromatic emission. A variety of lasers have been used in research for hyperspectral fluorescence and Raman imaging for the inspection of food and agricultural commodities (Kim et al., 2003; Noh and Lu, 2007; Qin et al., 2010). Other types of light sources such as ultraviolet (UV) fluorescent lamps (Kim et al., 2001), narrowband LEDs (Qin et al., 2011), high-pressure arc lamps (e.g., xenon), and low-pressure metal vapor lamps (e.g., mercury) can also serve as excitation sources.

3.2. Wavelength dispersive devices

Wavelength dispersive devices are the core component of spectral imaging systems. Their function is to disperse broadband light into different wavelengths and project the dispersed light to the area detectors. Many optical and electro-optical instruments can be used for this purpose. The common dispersive devices are presented in the following sections.

3.2.1. Imaging spectrographs

An imaging spectrograph is an optical device that disperses broadband light into different wavelengths from different spatial regions of a target. It differs from the traditional spectrograph in that it can also carry spatial information. Most imaging spectrographs are built based on diffraction gratings, which include two major types: transmission and reflection gratings.

Fig. 3a shows the operating principle of a transmission-grating-based imaging spectrograph. Specifically, it is built using a prism-grating-prism (PGP) component. Incoming light from the entrance slit is collimated by the front lens. The collimated beam is dispersed at the PGP component, where the direction of light propagation is dependent on its wavelength. The central wavelength passes symmetrically through the PGP, while the shorter and longer wavelengths are dispersed up and down relative to the central axis. As a result, the light from the scanning line is dispersed into different wavelengths. The dispersed light is then projected onto an area detector through the back lens, creating a special 2-D image: one dimension represents spatial and the other spectral. The operating principle of a reflection-grating-based imaging spectrograph is illustrated in Fig. 3b. The construction is based on an Offner configuration. The basic structure includes a pair of spherical mirrors coupled with a convex reflection grating. The lower mirror guides light from the entrance slit to the reflection grating, where the beam is dispersed into different wavelengths. The upper mirror then reflects the dispersed light to the detector, where a continuous spectrum is formed.

Both types of the imaging spectrographs can be attached to a lens and an area detector to form a line-scan spectral camera system. During the past decade, the imaging spectrographs have been widely used to develop various line-scan spectral imaging systems for research and industrial applications in the area of food safety and quality inspection (Kim et al., 2001; Park et al., 2002; Lu, 2003; Chao et al., 2008). Fig. 4 illustrates a line-scan hyperspectral reflectance/fluorescence system that uses an Offner imaging spectrograph (Kim et al., 2011). A hypercube is built up as the positioning stage moves the samples transversely through the scanning line. The field of view of the system is adjustable (i.e., 80-
300 mm) to accommodate imaging of items from individual wheat grains to whole chicken carcasses. The acquired hyperspectral images can be used for evaluating physical, chemical, and biological properties of various food and agricultural products.

3.2.2. Electronically tunable filters

An electronically tunable filter changes the bandpass wavelength via electronic devices. There are two major types of tunable filters: acousto-optic tunable filters (AOTFs) and liquid crystal tunable filters (LCTFs).

An AOTF is a solid-state device that isolates a single wavelength from broadband light based on light-sound interactions in a crystal. Fig. 5a illustrates the operating principle of an AOTF. An acoustic transducer generates high-frequency acoustic waves through the crystal, which changes the refractive index of the crystal. The variations of the refractive index make the crystal behave like a transmission diffraction grating. Light is diffracted into two first-order beams with orthogonal polarizations. The zero-order beam and the undesired diffracted beams are blocked by the beam stop. The AOTF only diffracts light at one particular wavelength at a time. The isolated wavelength is a function of the frequency of the acoustic waves. Thus, the passing wavelength can be controlled by varying the frequency of the RF source.

An LCTF is a solid-state device utilizing electronically controlled liquid crystal cells to transmit light at a specific wavelength. The LCTF is constructed by a series of optical stacks, each consisting of a retarder and a liquid crystal layer between two polarizers (Fig. 5b). The incident light is polarized through the polarizer and then separated into two rays by the retarder. The separated rays emerge with a phase delay that is dependent upon the wavelength. The polarizer behind the retarder only transmits wavelengths in phase to the next stage. Each stage transmits light as a sinusoidal function of the wavelength. The transmitted light adds constructively in the desired bandpass and destructively in the other spectral regions. All the stages function together to transmit a single wavelength. The controller can shift the narrow bandpass region by applying an electric field to each liquid crystal layer.

The electronically tunable filters can switch between wavelengths much faster than mechanical devices such as filter wheels. Other advantages include high optical throughput, narrow bandwidth, broad spectral range, accessibility of random wavelength, and flexible controllability and programmability (Morris et al., 1994). The AOTFs and LCTFs have been used to develop area-scan spectral imaging systems for many agricultural applications (Peng and Lu, 2006; Safren et al., 2007; Zhang et al., 2007; Gómez-Sanchis et al., 2008; Wang et al., 2012).

3.2.3. Beam splitting devices

Beam splitting devices can simultaneously acquire narrowband images at more than one selected wavelength. Their function is to divide light into two or more parts. The useful wavelengths are predetermined, and the corresponding bandpass filters are placed on the paths of the separated beams. The divided scenes pass through the filters separately, and the single-band images are formed either on one camera with a large CCD sensor or on several cameras. Depending on the wavelength constitution of each separated beam, the beam splitting devices can be classified into two categories: color splitting and neutral splitting. The color splitting devices guide particular wavebands to each output, while the neutral splitting devices guide particular portions of the total light energy to each output.
Fig. 6 shows two example neutral beam splitting devices. Fig. 6a is a two-channel plate beamsplitter. Light with a 45° angle of incidence is divided into two portions after hitting the plate painted with separation coatings. If the splitting plate is replaced by a cold mirror or a hot mirror, the unit becomes a color splitting device since a cold mirror reflects visible and transmits infrared and a hot mirror does the opposite. Fig. 6b is a three-channel prism beamsplitter. The unit consists of three prism components that are cemented together by two neutral films. The incoming light is separated into three parts after interacting with the neutral films and the hypotenuses of the prisms. After passing through three preset filters, light will form three narrowband images on three detectors for the same scene.

Beam splitting devices can be used to build multispectral imaging systems. Systems with two or three bands may be sufficient for certain applications using simple detection algorithms. More image channels can be achieved by using more complicated separation prisms or combining color and neutral splitting devices (Kise et al., 2010). The multispectral imaging systems based on beam splitting devices have found many agricultural applications, especially for real-time and online inspection tasks (Aleixos et al., 2002; Kleynen et al., 2005; Kise et al., 2007; Lu and Peng, 2007; Park et al., 2007a,b; Qin et al., 2012).

3.3. Area detectors

The light carrying the sample information is eventually collected by an area detector. Currently CCD (charge-coupled device) cameras are the mainstream devices used in spectral imaging systems. The CCD sensor is composed of many small photodiodes (called pixels) that are made of light-sensitive materials, such as silicon (Si) or indium gallium arsenide (InGaAs). Each photodiode converts incident photons to electrons, generating an electrical signal proportional to total light exposure. The spectral response of the CCD sensor, which is quantified by its quantum efficiency (QE), is primarily governed by the substrate materials used to make the photodiodes.

3.3.1. Silicon CCD cameras

Owing to its natural sensitivity to visible light, silicon is intensively used as sensor material for making cameras that work in the visible and short-wavelength near-infrared regions. A typical QE curve of silicon CCD cameras is shown in Fig. 7a. The spectral response of the silicon sensors is generally a bell-shaped curve with QE values declining towards both ultraviolet and near-infrared regions. The silicon CCD cameras have been widely used in various spectral imaging systems working in the visible and short-wavelength near-infrared regions (Kim et al., 2001; Park et al., 2002). Low-light imaging applications and fast spectral image acquisitions usually need high-performance cameras such as Electron-Multiplying CCD (EMCCD) cameras (Chao et al., 2008; Kim et al., 2011; Qin et al., 2011).

3.3.2. InGaAs CCD cameras

For working in the near-infrared region, InGaAs, an alloy of indium arsenide (InAs) and gallium arsenide (GaAs), is the common

![Fig. 6. Beam-splitting devices for multispectral imaging. (a) a two-channel plate beamsplitter and (b) a three-channel prism beamsplitter.](image)

![Fig. 7. Quantum efficiencies of (a) silicon CCD and (b) InGaAs CCD area detectors.](image)
substrate material of the image sensors. A typical QE curve of InGaAs detectors is shown in Fig. 7b. The InGaAs detectors have fairly flat and high QE in the near-infrared region. Standard InGaAs sensors cover the spectral region of 900–1700 nm. An extended wavelength range (e.g., 1100–2600 nm) can be achieved by changing the percentages of InAs and GaAs for making the sensors. The InGaAs CCD cameras have been used in spectral imaging systems that work in the near-infrared wavelength ranges (Lu, 2003; Nicolaï et al., 2006).

4. Calibration of spectral imaging systems

Spectral imaging systems obtain rich raw information from the target. Appropriate calibration is an essential step for acquiring meaningful image data. The commonly used calibration methods are presented in the following sections.

4.1. Spectral calibration

Spectral calibration for hyperspectral/multispectral imaging systems aims to define the wavelengths for the pixels along the spectral dimension of the image data. The calibration results can be used to determine the range and the resolution of the spectral information. The area-scan systems using electronically tunable filters collect single-band images at a series of known wavelengths. The passing wavelengths are determined by their electronic controllers. Therefore the wavelength calibration is usually not necessary for the area-scan systems.

The line-scan systems using imaging spectrographs acquire images with unknown wavelengths. Spectral calibration is needed to map the pixel indices along the spectral dimension of the detector to the wavelengths. The calibration can be performed using spectrally established light sources, such as calibration lamps and lasers. The calibration lamps are the most common calibration sources. They generate narrow spectral lines from the excitation of rare gases and metal vapors (e.g., argon, krypton, neon, xenon, mercury, mercury–argon, mercury–neon, and mercury–xenon). Fig. 8 shows an example of spectral calibration for a line-scan hyperspectral imaging system. Two pencil-style calibration lamps (xenon and mercury–argon lamps, Newport, Irvine, CA, USA) provided several good peaks in the spectral region of 400–1000 nm. Spectral profiles were extracted along the vertical axis of each line-scan image. The pixel positions and the corresponding wavelengths were identified, and their relationship was established.

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**Fig. 8.** Spectral calibration for a line-scan hyperspectral imaging system using calibration lamps. (a) Line-scan images, (b) spectral profiles, and (c) a linear regression model.
using a linear regression function. Nonlinear regression models can also be used for the spectral calibration (Park et al., 2002; Chao et al., 2008).

4.2. Spatial calibration

Spatial calibration is performed to determine the range and the resolution of the spatial information. The calibration results are useful for adjusting the field of view and estimating the spatial detection limit. The spatial resolution of a point-scan system is determined by the step sizes used for the two scan directions, while the spatial range is determined by the combination of the step sizes and the scan numbers. For line-scan systems, the spatial resolution for the scan direction depends on the step size of the movement. The resolution for the direction parallel to the slit is determined by a combination of factors involving working distance, lens, imaging spectrograph, camera, etc. The spatial calibration for area-scan systems can be performed at a selected wavelength using printed targets with square grids or standard test charts.

Fig. 9 demonstrates examples of spatial calibrations for three hyperspectral systems. Fig. 9a shows an image of a standard test chart acquired by a point-scan Raman imaging system (Qin et al., 2010). The diameter for the smallest dots is 0.25 mm, and the distance between these adjacent dots is 0.50 mm. The outermost large dots are positioned within a 50 mm square. A step size of 0.1 mm was used to scan both x and y directions. The 0.25 mm dots can be clearly discerned owing to the small step sizes used to scan the chart. Fig. 9b is a 256 × 256 line-scan image of a piece of white paper printed with parallel lines spaced 2 mm apart. The image was obtained by a hyperspectral system designed for light scattering measurement (Qin and Lu, 2008). The step size is 1.0 mm. Hence the spatial resolution for the x direction (see Fig. 1) is 1.0 mm/pixel. The resolution for the y direction can be determined by dividing the distance by the number of pixels in this range. The spatial resolution can be calculated as 30 mm/150 pixels = 0.2 mm/pixel. Fig. 9c shows an area-scan image of a piece of white paper printed with a 10-mm square grid, collected by an LCTF hyperspectral system. Similarly, the spatial resolution can be calculated as 90 mm/225 pixels = 0.4 mm/pixel.

4.3. Image registration

For imaging systems using beam-splitting devices, image misalignment usually occurs due to various factors associated with imperfections in the system, such as lens distortions, positional tolerance of the CCD sensors, different sensor types, and differences among the mechanical parts. Image registration is usually needed to align two or more images. Typically, one image (the base image) is selected as the reference, to which other images (input images) are compared. The goal of image registration is to align the input images with the base image by applying necessary spatial transformations, such as image flip, translation, rotation, crop, scaling, and shearing. The parameters of spatial transformation can be determined through mapping the locations of selected control points from a pair of base and input images. A calibration template is usually used in this process. The transformations and the corresponding parameters are then saved for transforming images collected in the future.

An example of image registration is shown in Fig. 10. The images were obtained by a two-channel beamsplitter-based imaging system (Fig. 6a), which was built for real-time detection of citrus surface disease (Qin et al., 2012). A calibration template was created by printing a grid of black dots with 10-mm spacing on a piece of white paper. The template image from ‘Camera 1’ was used as the base image, and the image from ‘Camera 2’ was used as the input image. Image calibration functions in LabVIEW Vision Development Module were used to align the two images. The parameters determined from the template images were used to register the images from the citrus samples. The two original images in Fig. 10 were acquired by two cameras at two bands for a citrus sample on a 5-fruits/s processing line. The overlap of the original images from the two cameras clearly reveals the misalignment. After image registration, the double image disappeared and only one fruit is observed in the overlay of the registered images.

5. Spectral images and analysis techniques

Three-dimensional spectral images provide a large amount of spatial and spectral information. Spectral image analysis, which involves both chemometrics and image processing techniques, is crucial to obtaining useful information for hyperspectral/multi-
spectral imaging applications. The common spectral image analysis methods are presented in the following sections.

5.1. Spectral image data

In general, 3-D spectral image data acquired by point-scan, line-scan, and area-scan methods are stored in the formats of Band Interleaved by Pixel (BIP), Band Interleaved by Line (BIL), and Band Sequential (BSQ), respectively. BIP format stores the first pixel of all the bands, followed by the second pixel of all the bands in sequential order, etc. BIL format stores all the bands for the first line, followed by all the bands for the second line in sequential order, etc. BSQ format stores the spatial image of each band in sequential order. The BIP and BSQ formats offer optimal perfor-

![Image registration for two narrowband images acquired by a beamsplitter-based two-band imaging system developed for real-time detection of citrus surface disease.](image)

![Representative hyperspectral images acquired by different methods.](image)

Fig. 10. Image registration for two narrowband images acquired by a beamsplitter-based two-band imaging system developed for real-time detection of citrus surface disease.

Fig. 11. Representative hyperspectral images acquired by different methods. (a) point-scan Raman images of a milk-melamine mixture, (b) line-scan fluorescence images of chicken blood on stainless steel, (c) LCTF-based area-scan reflectance images of a diseased leaf using an LCTF, and (d) line-scan scattering images of tomatoes at different ripeness stages.
mance for spectral and spatial accesses, respectively. The BIL format gives a compromise in performance between spatial and spectral analysis.

Fig. 11 shows representative hyperspectral images from different acquisition methods. The images in Fig. 11a, b, and c were collected using point-scan Raman, line-scan fluorescence, and area-scan reflectance methods, respectively. The images in Fig. 11d are light scattering images, which were acquired by scanning a sample surface along a line of points increasingly distant from the point of illumination. The scattering images aim to reveal the internal light-scattering patterns of the tomatoes, which can provide useful information for evaluating internal qualities of food and agricultural products (Qin and Lu, 2008).

5.2. Spectral image analysis

Main procedures for analyzing hyperspectral and multispectral images are summarized in Fig. 12. Hyperspectral images contain redundant information across tens or hundreds of bands. The key for hyperspectral image analysis is to reduce the spectral dimension and extract useful information for qualitative/quantitative analysis. A subset containing a few significant wavebands can be redundant information across tens or hundreds of bands. The key for hyperspectral image analysis is to reduce the spectral dimension and extract useful information for qualitative/quantitative analysis. A subset containing a few significant wavebands can be identified during this process, and then adopted by a multispectral imaging solution for online and real-time inspection tasks using a simple algorithm.

5.2.1. Data preprocessing

Raw spectral images contain noise, artifacts, and useless signals due to aspects of the measurement environment and imperfect system components. During image acquisition, the noise counts are accumulated on the detector, which increases the pixel values beyond their true intensities. Many factors, such as non-uniform illumination, dust on the lens surface, or pixel-to-pixel variations of the CCD, can cause various image artifacts. Undesired signals may also be collected with the useful data. All these factors make the original images unsuitable for qualitative/quantitative analysis. The intent of preprocessing is to remove these effects and make the data independent of the imaging systems and the measurement conditions.

Flat-field correction is a common preprocessing method for reflectance measurements. White diffuse reflectance panels with high, flat reflectance attributes over a broad spectral region are usually used as standards. The correction can be conducted using the following equation:

\[
Rs(\lambda) = \frac{Is(\lambda) - Id(\lambda)}{Ir(\lambda) - Id(\lambda)} \times Rr(\lambda)
\]

where \(Rs\) is the relative reflectance image of the sample, \(Is\) is the intensity image of the sample, \(Ir\) is the reference image of the white panel, \(Id\) is the dark current image acquired with the light source off and the lens covered, \(Rr\) is the reflectance factor of the white panel, and \(\lambda\) is the wavelength. In practice, a constant reflectance factor (RR) of 100% for all wavelengths is usually used for simplification. Because most food and agricultural products have lower reflectance than the white panel has, the relative reflectance values calculated by Eq. (1) are usually in the range of 0–100%. They can be multiplied by a constant factor (e.g., 10,000) to increase the dynamic range and to reduce the rounding errors. The relative reflectance instead of the absolute intensity is usually used for further analysis. Besides the flat-field correction, other preprocessing methods such as spectral smoothing, normalization, baseline correction, image masking, and spatial filtering can be used to deal with various undesirable artifacts and noise found in the spectral images.

5.2.2. Spectral dimension reduction and band selection

Since hyperspectral images can be viewed as numerous spatially organized spectra, many chemometric methods and multivariate analysis techniques, such as spectral matching method, principal component analysis (PCA), partial least squares (PLS), artificial neural networks (ANN), linear discriminant analysis (LDA), and correlation analysis (CA), can be used for spectral analysis and dimension reduction. To facilitate spectral analysis, spectra can be extracted from regions of interest (ROIs) from particular image areas. The whole hyperspectral image can also be unfolded and reshaped to form a 2-D spectral matrix, on which multivariate analysis methods can be performed directly. The results can generally be folded back to the image format.

In many hyperspectral applications, it is necessary to identify target pixels on the sample surfaces. Spectral matching algorithms are usually used to perform statistical comparisons between reference spectra and unknown spectra extracted from the hyperspectral images. Various spectral similarity measures have been developed for target detection and spectral classification. Choices for such metrics include spectral angle mapper (SAM), spectral correlation mapper (SCM), Euclidean distance (ED), and spectral information divergence (SID) (Chang, 2000). SAM, SCM, ED, and SID calculate angle, correlation, distance, and divergence between two spectra, respectively. The smaller the values of these metrics, the smaller the differences between two spectra. In general, a reference spectrum is established first, and it is used to calculate a selected similarity metric for each hyperspectral pixel. As a result, a 2-D rule image is generated, which can be used for image classification. The spectral matching methods have been used for spectral dimension reduction and target identification in various hyperspectral applications (Park et al., 2007a,b; Qin et al., 2009).

Fig. 13 demonstrates an example of using SID mapping to reduce the spectral dimension of the hyperspectral images. The images were collected from reflectance measurement of grapes in the wavelength range of 450–930 nm (92 bands) for detecting a particular disease (i.e., canker) on the fruit peel (Qin et al., 2009). ROIs of canker were first selected from the images of reference samples. A mean spectrum, calculated from the spectra extracted from all the canker ROIs, was used as the reference spectrum. SID mapping was then performed on the hyperspectral images of the test samples to obtain the rule images. Finally, a simple thresholding method was applied to the rule images to separate canker lesions from the fruit peel and other surface diseases.

The spectral matching example in Fig. 13 reduces 92 bands to one band by using all the spectral information, which however does not provide important wavelengths. PCA, on the other hand,
is a useful tool that cannot only reduce the spectral dimension but also identify important bands. The basic idea of PCA is to find far fewer components through orthogonal transformation to maximize representation of the original data. The redundant data can thus be largely reduced by observing few scores without significantly losing useful information. Loadings of PCA can be used to identify important variables (e.g., wavelengths). When PCA is used for hyperspectral images, the 3-D data are usually unfolded first to form a 2-D matrix, on which PCA can be performed in a similar manner as for regular spectral data. After PCA, each score vector for the selected principal components (PCs) is folded back to form a 2-D score image. PCA and other similar methods [e.g., independent component analysis (ICA) and minimum noise fraction (MNF) transform] have been widely used for analyzing hyperspectral images and determining important wavelengths (Kim et al., 2002; Park et al., 2002; Lu, 2003; Zhu et al., 2007).

Fig. 13. Spectral information divergence (SID) mapping for reducing the spectral dimension of the hyperspectral reflectance images of a grapefruit sample and identifying canker disease on the fruit peel.

Fig. 14 shows an example of using PCA to reduce the spectral dimension and identify the important bands. The hyperspectral reflectance images were acquired from grapefruits in the spectral region of 400–900 nm (99 bands) for canker detection (Qin et al., 2008). PCA was performed using all 99 wavelengths. The first four score images demonstrated different patterns for the fruit. The score images of the fifth PC and after did not provide meaningful information. The PC-3 images showed great potential for canker detection and were used for further image classification. Four important bands were identified at two local maxima and two local minima on the PC-3 loading curve, and they have the potential to be used in a multispectral algorithm for canker detection.

Besides the methods discussed above, many other multivariate analysis techniques can be used to reduce spectral dimension and identify important wavelengths (Grahn and Geladi, 2007). Examples include correlation analysis (CA) (Lee et al., 2008), artificial intelligence (AI) methods, and machine learning algorithms (Park et al., 2002; Lu, 2003; Zhu et al., 2007).
neural network (ANN) (Bajwa et al., 2004), genetic algorithm (GA) (Xing et al., 2008), sequential forward selection (SFS) method (Nakariyakul and Casasent, 2008), etc. After the spectral dimension reduction, image postprocessing operations (e.g., thresholding, morphological filtering) are usually followed to produce the final results (e.g., identification, classification, and mapping) for qualitative/quantitative analysis. Simple algorithms (e.g., band ratio) can be developed based on the selected bands for multispectral imaging applications.

5.3. Spectral image analysis software

Various software packages are available to facilitate spectral image analysis. One of the most popular packages used in hyperspectral imaging community is Environment for Visualizing Images (ENVI) (ITT Visual Information Solutions, Boulder, CO, USA). ENVI is a powerful tool for hyperspectral/multispectral image analysis and provides numerous functions for data transformation, filtering, classification, mapping, visualization, etc. Fig. 15 shows a snapshot of the ENVI's user interface when used for analyzing hyperspectral reflectance images of diseased citrus samples. As shown in Fig. 15, the single-band images can be displayed at selected bands. The spatial and the spectral profiles can be extracted and plotted at a selected pixel. Various image processing operations (e.g., masking, band ratio, thresholding, and morphological filtering) can be used to generate the final classification result. Other similar packages include HyperCube (U.S. Army Geospatial Center, Alexandria, VA, USA), Hyperspec (Headwall Photonics, Fitchburg, MA, USA), and MIA_Toolbox (Eigenvector Research, Wenatchee, WA, USA), etc. Besides the existing software, spectral image processing routines can also be developed using computer programming languages, such as MATLAB, C/C++, Visual Basic, and LabVIEW.

6. Applications for food safety and quality evaluation

As an emerging sensing technique, hyperspectral imaging equips conventional spectroscopy with the capability of spatial information acquisition, which greatly enhances detection abilities and expands the application scope. During the past decade, hyperspectral imaging has been intensively explored for analyzing physical, chemical, and biological properties of a broad range of food and agricultural products. Table 1 summarizes main hyperspectral imaging applications in the area of safety and quality evaluation of food and agricultural products. As shown in Table 1, food surface inspection is a major application area. Reflectance and fluorescence spectral information in the visible and near-infrared region is widely used to inspect external features of different types of products. Imaging-spectrograph-based line-scan systems are used as major hyperspectral imaging tools, while area-scan systems using electronically tunable filters are also utilized in many applications. When it comes to the inspection of internal attributes, transmittance measurement is usually performed using high-intensity light sources. Light scattering technique provides another approach for internal quality evaluation. Also, combining different image acquisition methods (e.g., reflectance/transmittance and reflectance/fluorescence) can give the systems more inspection capabilities than systems that use only a single imaging mode may have. Such image acquisition combinations along with data fusion techniques.

Fig. 15. ENVI software for hyperspectral image analysis of citrus surface diseases.
Multispectral imaging applications for food and agricultural products.

Bandpass filters with the nearest central wavelengths to the identified important bands are used in these area-scan systems to obtain the narrowband images. The filters can be physically changed to different central wavelengths and bandwidths for different applications. On the other hand, line-scan imaging systems that can work in both hyperspectral and multispectral modes have recently been developed (Chao et al., 2008; Kim et al., 2008). The multispectral imaging mode allows flexible selection for the number of bands, the central wavelengths, and the bandwidths through software control. With the help of the low-light detection ability of EMCCD cameras, such systems are able to scan hundreds of lines per second using exposure times at the millisecond level, making them especially suitable for real-time inspection of fast-moving food items on the processing lines. The fast line-scan spectral

Table 1

<table>
<thead>
<tr>
<th>Class</th>
<th>Product</th>
<th>Application</th>
<th>Image acquisition method</th>
<th>Wavelength (nm)</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Apple</td>
<td>Bitter pit detection</td>
<td>Line-scan reflectance</td>
<td>954–1350</td>
<td>Nicolai et al. (2006)</td>
</tr>
<tr>
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<td>Apple</td>
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<td>Line-scan reflectance/fluorescence</td>
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<td>Kim et al. (2007)</td>
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<td>400–1000</td>
<td>Rajkumar et al. (2012)</td>
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<td>625–774</td>
<td>Vargas et al. (2005)</td>
</tr>
<tr>
<td></td>
<td>Cherry</td>
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<td>Line-scan transmittance</td>
<td>450–1000</td>
<td>Qin and Lu (2005)</td>
</tr>
<tr>
<td></td>
<td>Citrus</td>
<td>Rottenness detection</td>
<td>Area-scan reflectance</td>
<td>460–1020</td>
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<tr>
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</tr>
<tr>
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<td>Peach</td>
<td>Firmness evaluation</td>
<td>Line-scan scattering</td>
<td>500–1000</td>
<td>Lu and Peng (2006)</td>
</tr>
<tr>
<td></td>
<td>Strawberry</td>
<td>Quality evaluation</td>
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<td>ElMasry et al. (2007)</td>
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<td>Ariana and Lu (2008)</td>
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<td>Pork</td>
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<td>408–1117</td>
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</tr>
</tbody>
</table>

Table 2

Multispectral imaging applications for food and agricultural products.

<table>
<thead>
<tr>
<th>Product</th>
<th>Application</th>
<th>Image acquisition method</th>
<th>Wavelength (nm)</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Apple</td>
<td>Surface defect detection</td>
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<td>740, 950</td>
<td>Bennedsen et al. (2005)</td>
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<tr>
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<td>Area-scan reflectance</td>
<td>430, 500, 750, 800</td>
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<tr>
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<td>Lu and Peng (2007)</td>
</tr>
<tr>
<td>Apple</td>
<td>Defect and feces detection</td>
<td>Line-scan reflectance/fluorescence</td>
<td>530, 665, 750, 800</td>
<td>Kim et al. (2008)</td>
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<td>Area-scan reflectance</td>
<td>495, 535, 585, 605</td>
<td>Chao et al. (2001)</td>
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<td>Area-scan reflectance</td>
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<td>Chao et al. (2008)</td>
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<td>Citrus</td>
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<td>Qin et al. (2012)</td>
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<td>Maturity evaluation</td>
<td>Area-scan reflectance</td>
<td>530, 595, 630, 850</td>
<td>Hahn (2002)</td>
</tr>
</tbody>
</table>
imaging technique represents a new direction in the area of online food inspection, and it has great potential to be adopted by food processing industries in the future.

Commercial hyperspectral/multispectral imaging systems for food and agricultural applications [e.g., Hyperspec Inspector produced by Headwall Photonics (Fitchburg, MA, USA) and SisuCHEMA produced by Specim (Oulu, Finland)] started appearing on the market in recent years. Such integrated systems generally include essential components in a whole package (e.g., light source, wavelength dispersive device, camera, embedded computer, hard drive, and software) for implementation of spectral imaging techniques. The commercialization of the spectral imaging systems will broaden the scope of the applications for food safety and quality evaluation.

7. Conclusions

Hyperspectral and multispectral imaging technologies are well suited for safety and quality evaluation of food and agricultural products. Building a working spectral imaging system involves many theoretical and practical aspects. Factors that must be considered for using hyperspectral/multispectral imaging in practice include spectral image acquisition methods, components for building spectral imaging system, methods for calibrating spectral imaging system, and techniques for analyzing spectral images. Common practices in the field and applications for inspecting food and agricultural products were reviewed to reflect the current status of the spectral imaging techniques. Driven by both academic and industrial forces in the food and agricultural areas, spectral imaging technologies have been developed rapidly during the past decade. Line-scan spectral imaging systems that can acquire hundreds of lines per second have been developed for online food inspection, and they have great potential to become the standard for a variety of routine uses in food processing plants. Imaging spectrographs that can scan more than 1000 lines per second are already available on the market. New hardware design concepts will be continuously introduced to produce improved and novel components for building high-performance systems. The fast-growing computing capacity of the computers will facilitate handling of large data files and processing spectral images in real time. Advances in both spectral imaging instruments and spectral image analysis techniques will propel the development of hyperspectral/multispectral imaging technologies in the future.

References


