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Food Safety Control Using Hyperspectral Imaging

Prathama V
Department of Computer Science and Engineering, BMS Institute of Technology and Management, Bangaluru, Karnataka, India

Dr. Thippeswamy G
Professor and Head, Department of Computer Science and Engineering, BMS Institute of Technology and Management, Bangaluru, Karnataka, India

ABSTRACT

Food safety and control is a great concern for the food industry, food-borne illnesses are burden on the public health, and can lead to the disturbance to the socity. This paper involves different types of hyperspectral imaging technologies used in the food safety and control for the food industry, and evaluation of food quality with an introduction, demonstration, summarization. Hyperspectral imaging is an emerging technology has been successfully devised in the food inspection and control. Additionally other studies, includes determination of physical, chemical and biological contamination in food production using hyperspectral imaging technology. The hyperspectral is an analysing tool for the food product inspection by offering spatial and spectral signals from food products. Hyperspectral imaging technology involves detection, classification and virtualization to qualify quality and safety attribute for the food seafty.

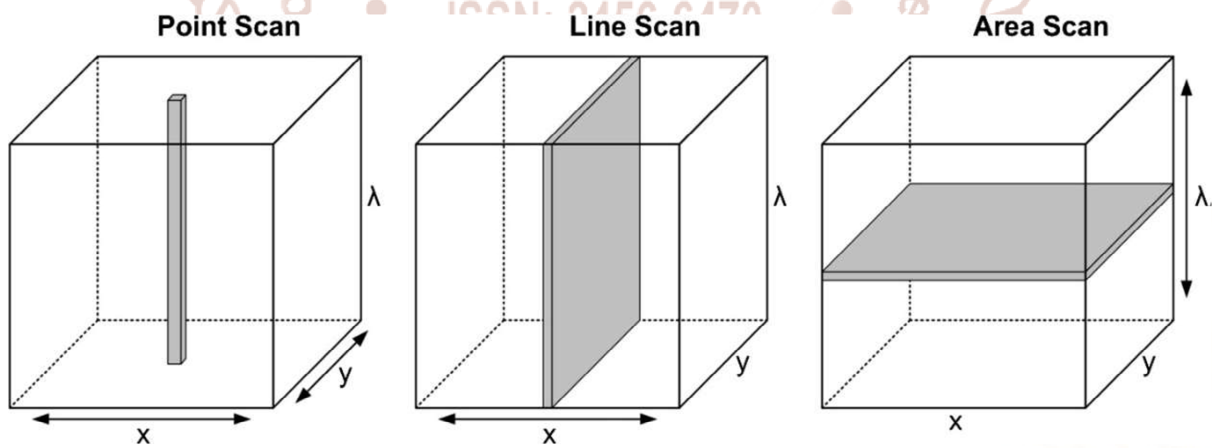
Keywords: *nondestructive method, hyperspectral imaging, chemical imaging, chemometrics, NIRS, computer vision, fluorescence, Raman, food safety, pathogen, contamination, fruits, vegetables, meat*

INTRODUCTION

Food industry is faced with a number of challenges, including maintenance of high-quality standards and assurance of food safety while avoiding liability issues. Meeting these challenges has become crucial in regards to grading food product for different market. Food safety is normally described as the converse of food risk, that is, a discipline aiming to ensure that food is safe enough “from-farm-to-fork” for consumers so that outbreaks of food-borne illness can be reduced. The content of food safety involves a wide range: physical, chemical, and biological contamination and other associated hazards or poisons. Quality and safety are usually defined by physical attributes (e.g.,texture, color, marbling), chemical attributes (e.g., fat, moisture, protein contents, pH, drip loss), and biological attributes (e.g., total bacterial count).Any occurrence of food safety problems always brings substantial influence to the society, and governing bodies worldwide are taking strict measures to implement effective practices and policies for the surveillance of the food industry. Therefore, it is desirable to develop an accurate, non-destructive, and real-time technique for food quality and safety assessment. Vibration spectroscopy (Sun, 2009) is an optical technology that depends on the interaction between incident light and molecules in matters. Because different molecules are sensitive to light with different wavelengths in terms of light absorption or scattering, the resultant spectra then record the information of these molecules over corresponding wave lengths In order to obtain spatial information, another technology, that is, computer vision is available. Computer vision (Sun, 2008) imitates the principle of human vision, using three bands (red, green, and blue) to acquire the characteristics of objects. Working in visible range, the features obtained by computer vision include shape, color, size, and texture However, only occasionally is this method reported to be sufficient for detecting chemical and biological parameters Both spectroscopy and computer vision techniques have found a wide range of applications in the food industry. The technique was originally developed for remote sensing applications as a mean of overcoming the limitations of spectroscopic and machine vision technique. With recent advancements in computer technology and instrumentation engineering, there have been significant advancements in techniques for assessment of food quality and safety. As an integrated alternative, hyperspectral imaging (HSI) can obtain both spectral and spatial information from the targets. As a result, the merits in spectroscopy and computer vision are both reflected in hyperspectral imaging. Furthermore, besides these aggregated advantages from both methods, more benefits are produced.

Hyperspectral Imaging System

Hyperspectral imaging (HSI) combines traditional imaging and spectroscopy technology and can be used to obtain spectral and spatial information of an object of interest over the ultraviolet, visible, and near-infrared spectral regions (200 nm-12 μm). Hyperspectral imaging systems provide hyperspectral images consisting of numerous spatial images of the same object at different wavelengths. Hyperspectral image, also called *hypercube*, is a three-dimensional data cube which is achieved through the superimposition of the spatial images collected by the hyperspectral sensors. These images are composed of vector pixels, and represent the composition and appearance of that particular food sample. Spectra from the data cube of different samples can be compared. Similarity between the image spectra of two samples indicates similarity of chemical composition and physical features. The *hypercube* usually can be constructed in three ways: *area scanning*, *point scanning*, and *line scanning*. Due to the presence of conveyor belts (for in-line inspection) inmost food processing plants, *line scanning* is the preferred method of image acquisition. Generally, there are three approaches for acquiring 3-D hyperspectral cubes [hypercubes (x, y,k)]. These are point-scan, line-scan, and area-scan methods 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 spectrophotometere quipped with a point detector is used to acquire a singlespectrum for each pixel in the 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. 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.



Configuration of a hyperspectral imaging system

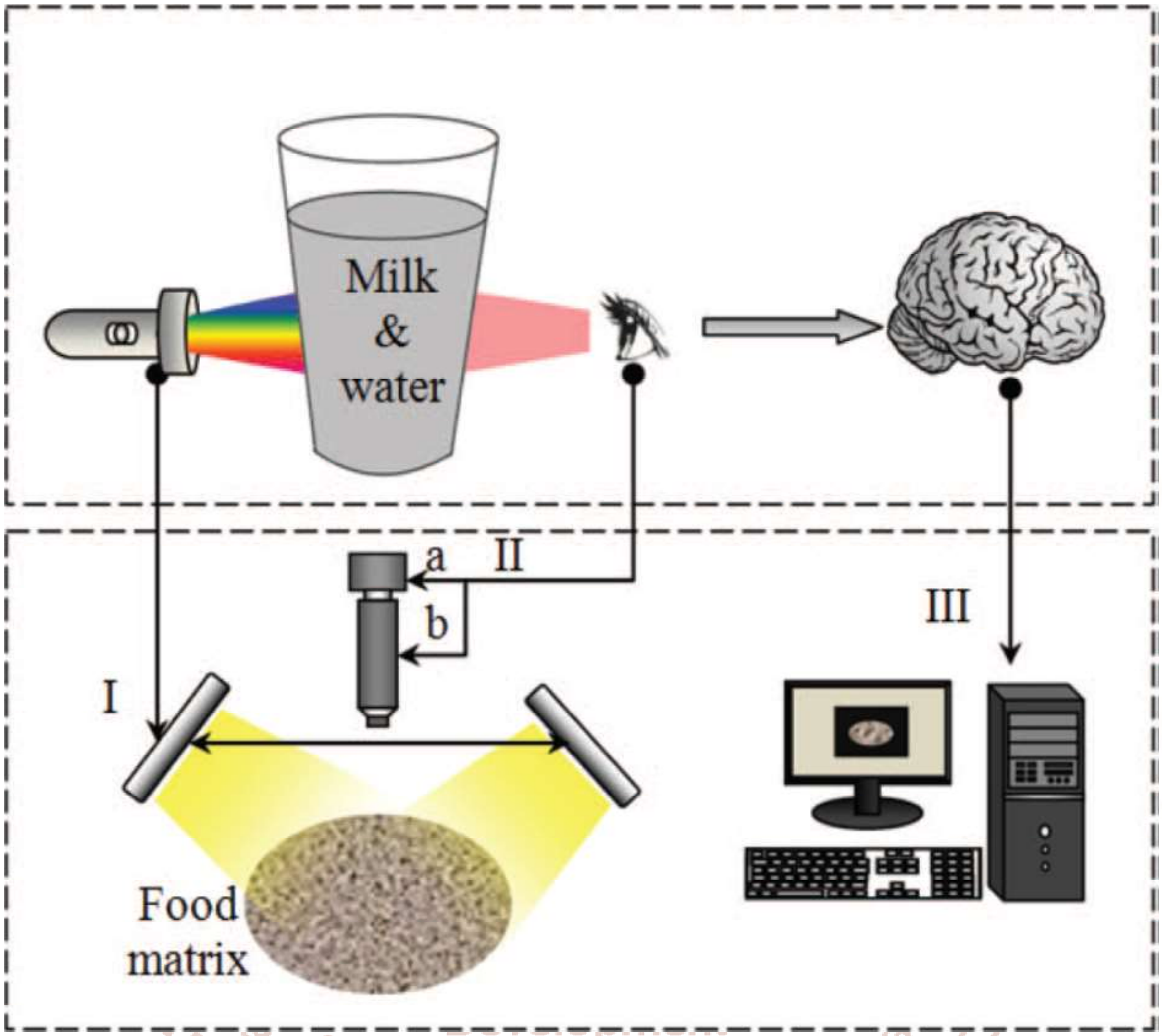
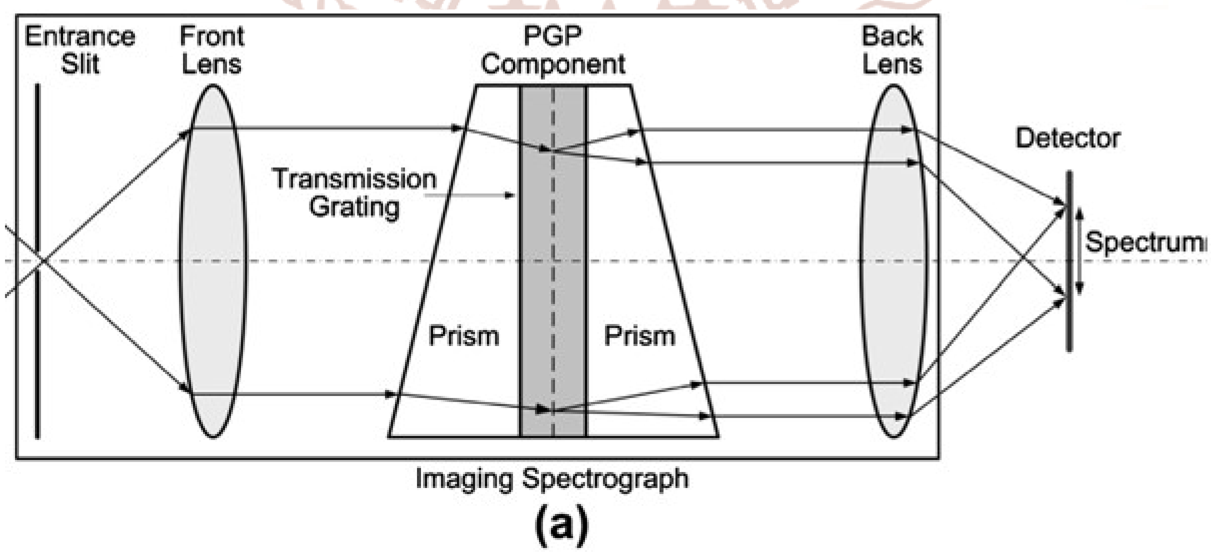


Figure 1 Configuration of a typical hyperspectral imaging system. I: light source; II: spectrograph (a: imaging unit; b: wavelength dispersion apparatus); III: information processor. (color figure available online.)

Detailed description of hyperspectral imaging systems



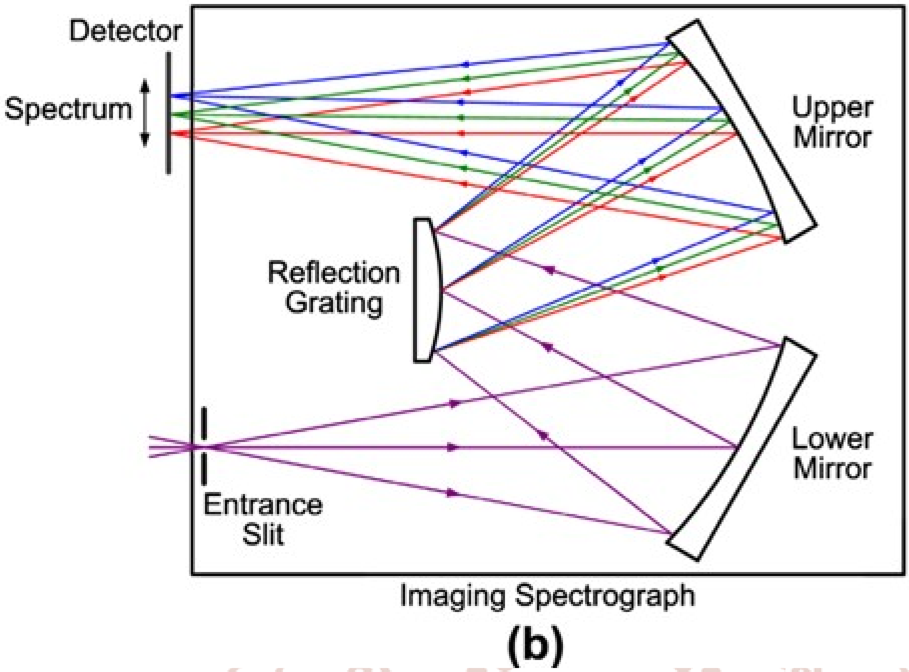


Figure 2: Wavelength-dispersive imaging spectrographs: (**a**) prism-grating-prism (PGP) transmission imaging spectrograph; and (**b**) Offner reflection imaging spectrograph.

As shown in Fig. 1, a hyperspectral imaging system consists of three main parts: a light source, a light dispersion device and imaging unit to function as the eye, and decision-making components such as computer hardware and software to function as the brain. The light provided by the light source interacts with the food samples, and the detected portion containing both physical and chemical information of the sample will be dispersed and projected onto a two-dimensional detector array in an imaging spectrograph, which serves the same role as human eyes do. The imaging spectrograph normally covers a wide range of both visible and near-infrared region; however, for human eyes, only three bands (red, green, and blue) are differentiated. The acquired

signal will then be transferred into a computer for further processing, including digitization, storage, modeling, and decision-making, in a similar way as the brain works. Detailed description of hyperspectral imaging systems can be found elsewhere (Sun, 2010). However, it should be noted that the wavelength dispersing apparatus sometimes are not necessary especially when developing MSI systems. For example, in multispectral imaging systems based on light-emitting diode(LED) light sources, the different individual wavelength band scan be obtained by switching on the corresponding LED sets Transmission and reflection gratings are two major types of diffraction gratings used in imaging spectrographs for wavelength dispersion. A transmission-grating-based imaging spectrograph is shown in Figure 2a. Incoming light is first collimated by a front lens and then dispersed at a prism-grating-prism (PGP) component, where light propagation direction is dependent on wavelength. The dispersed light is projected onto a detector through a back lens, creating a special 2-D image: one dimension represents spatial and the other spectral. Figure 2b shows a reflection-grating-based imaging spectrograph, which is specifically based on an Offner configuration. The spectrograph includes a pair of spherical mirrors and 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 for each spatial point along a scanning line on the sample. Dispersive imaging spectrographs are commercially available for different spectral regions, such as ultraviolet and visible (UV-VIS: 250–500 nm), visible (VIS: 380–800 nm), visible and near infrared (VNIR:400–1000 nm), near infrared (NIR: 900–1700 nm), short-wavelength infrared (SWIR: 1000–2500 nm),and mid-wavelength infrared (MWIR: 3000–5000 nm). Imaging spectrographs working in narrower wavelength ranges (e.g., Raman spectrographs in 770–980 nm) are also available for particular applications (e.g., high spectral resolution).

Analysis of hyperspectral images

The data cube produced by hyperspectral imaging systems contains a mass of information with large dimensionality. The main purpose of hyperspectral data analysis is to reduce the dimensionality and retain the useful data for discrimination or measurement analysis of food quality and safety.

Data Structure

The final data acquired by HSI systems are vividly called "hypercube" since they can be illustrated as containing three dimensions with two for spatial coordinates and the other one for spectral values. Accordingly, I(x, y, λ) is denoted, where x and y are used to locate the pixels in the image with λ for the wavelength. For the hypercube, if the wavelength λ is fixed, a matrix of spectral responses Iλ(x, y) is gained, and the visualization of this matrix produces a gray-level image of the object at the wavelength λ. It should be noted that the collective image (or image stack) for all wavelengths are intrinsically the same as a conventional digital image: they both offer optical perception in a spatial domain. The only difference is in the number of wavebands involved and therefore the amount of characteristic information provided. Particularly, for hypercubes, depending on the wavelength λ concerned, the object of interest may either be apparent to be recognized or merged in the background and noise, resulting in difficulties for identification. Therefore, efficient image analysis methods should be carefully developed and employed to sift useful bands, which will be discussed later. Also, the hypercube can be reconstructed as Ix(y, λ) or Iy(x, λ). In this way, at a fixed spatial coordinate of either x or y, another matrix indicating the distribution of spectra(covering all the available wavelengths λ) along the other spatial axis y or x can be obtained. In the resultant matrix, a vector is then the spectrum of a pixel. Therefore, the visualized "image" is within the spectrum-spatial domain, and is quite distinctive from the conventional image produced by computer vision. Specifically, a hypercube is the simultaneous display of the successively aligned spectra of their corresponding pixels in the object. The above two ways of understanding a hypercube is by breaking it up into slices, that is, to divide a three-dimensional matrix into a stack of two-dimensional matrix assigned to either spatial-spatial or spatial-spectral coordinate. Alternatively, a hypercube can also be considered as an organized combination of pixel-wise spectra, with the resulting donation as Ix, y (λ), as is illustrated in Fig.3

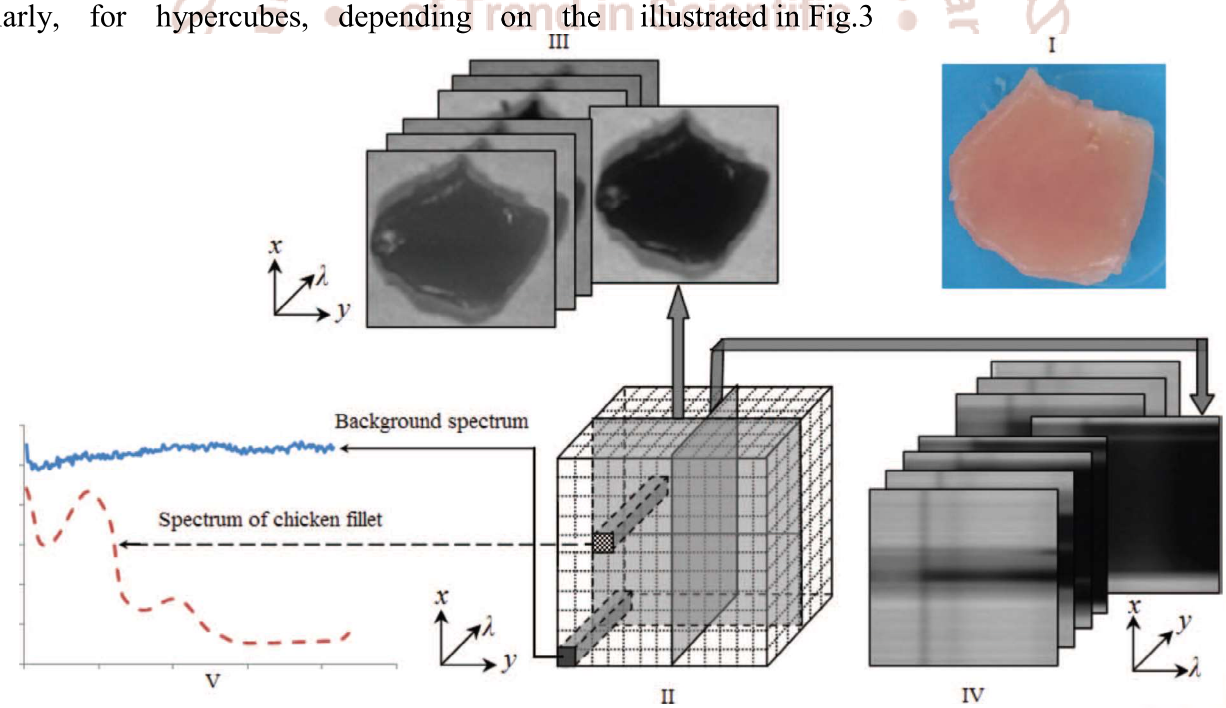


Figure 3 Different ways of understanding a hypercube. I: RGB image of a chicken breast fillet slice; II: the spatial structure of a hypercube; III: front view of the hypercube; IV: side view of the hypercube; V: Spectra of pixels in different portions. (color figure available online.)

The above three ways of interpretation of hypercubes correspond to different ways of data acquisition methods, that is, area scanning imaging (or staring imaging), line-scanning imaging(or pushbroom imaging), as well as point-scanning imaging (or whiskbroom imaging). In area-scanning imaging, the hypercube is obtained by gaining spatial images at all wavelengths in sequence, in line-scanning imaging pixel spectra are acquired line by line, while in point scanning, the spectra are obtained pixel by pixel. Nevertheless, among these three scanning approaches, pushbroom imaging is the most popular one in the food industry due to its readiness for on-line application. Under such a scanning scheme, the object needs to go with a translation stage and pass the field of view of the spectrograph where images are produced. Based on this, only a simple transfer, that is to replace the translation stage with a conveyor in processing line, is necessary for the on-line application.

Data Processing

Figure 4 illustrates the process of hyperspectral data analysis, including reflectance calibration, segmentation of ROI, image processing and spectral analysis, and classification (qualitative analysis) or prediction (quantitative analysis).

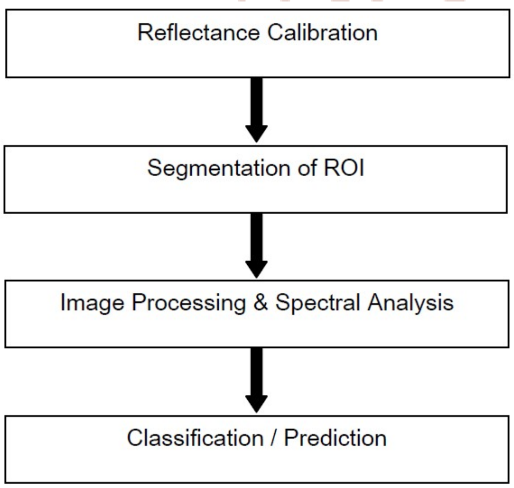


Figure 4: .Flow diagram of hyperspectral data analysis process

All hyperspectral images need to be corrected from the dark current of the camera prior to the following data analysis. At the stage of reflectance calibration, the dark response D and the bright response W are obtained respectively by covering the lens with the cap and by taking an image from uniform high reflectance standard (standard white reference). The corrected reflectance value R of the original reflected signal I is calculated on pixel-by-pixel basis as follows = $(I$ $-D)$ $(W$ $-D)$. After the reflectance calibration, the region of interest (ROI) will be segmented from the background for the further image processing and spectral analysis. Some image processing algorithms can be used to segment ROI, including thresholding, edge detection, filtering, mathematical morphological algorithm, and so on (Martin and Tosunoglu, 2000)

Image Correction

The raw images acquired by a HSI system in reflectance, transmittance, or scatter mode, are normally recorded in radiance. However, it is sensitive to the sensors used, which means that the images for the same sample taken under the same condition may differ according to the configurations of the HSI system employed (Yao and Lewis, 2010). To improve the comparability of the image data, radiometric calibration is often performed. Such calibration requires obtaining a dark current image (Idark) and white reference image (Iwhite).After that, the following is utilized for pixel-wise corrections.

$Ic = (I - Idark)/(Iwhite - Idark)$ (1)

Where I and Ic are sample images before and after correction. In Eq. (1), the operation in denominator is to eliminate the spatialnon-uniformity of the light source and the subtraction innumerator can reduce noise of the system. While as a whole, the percentage generated by division is capable of simplifying subsequent computations. More importantly, spectra from the calibrated images can be interpreted to allocate featured molecular bonds or components.

If no white reference standard is available, the equation below

Can then be employed, which is also applicable to Raman image

Correction (Qin et al., 2010):

$Ic = I - Idark$ (2)

In addition, Lambert's cosine law is effective in eliminating the effects from surface morphological variations of samples, especially those with spherical shapes (Qin and Lu, 2008). However, it is not necessarily applied in food inspection when using hyperspectral imaging. For images obtained in fluorescence mode, a different correction method is to be applied due to its different nature from reflectance. To implement such corrections, both reference and dark images are required. Particularly, in collecting reference images, three flat-field materials, that is, premium white inkjet paper, methanol solutions of fluoresce in, and rhodamine B aroused to account for spectral profiles in blue, green, and red regions, respectively (Kim et al., 2001b). During calibration, a Correction factor (CF) is calculated first for every pixel in the image

At a certain wavelength, and these factors are then multiplied to individual corresponding pixel of the dark-current-subtracted sample image. The whole procedure is expressed by Kim et al.(2001b) as follows:

$CF\lambda = (FRave, \lambda - FRdark, \lambda) / (FRi, \lambda - Fdark, \lambda)$ (3)

$FSci, \lambda = CF\lambda \cdot (FSi, \lambda - Fdark, \lambda)$ (4)

where CF λ represents the correct factors for image at wavelength λ; FRave, λ is the mean of all pixel responses in the reference image at wavelength λ; Fdark, λ is the dark image at wavelength λ; FRi, λ is the intensity of the ith pixel in the reference image at wavelength λ; FSc, λ and FS λ are corrected and uncorrected images of the same sample at wavelength λ.Additionally, FRave, λ should be constantly shifted to acquire radiance-corrected images. However, in case of studies where more interests are focused on the relative changes of the intensities, this step can be skipped.

Data Processing Routines

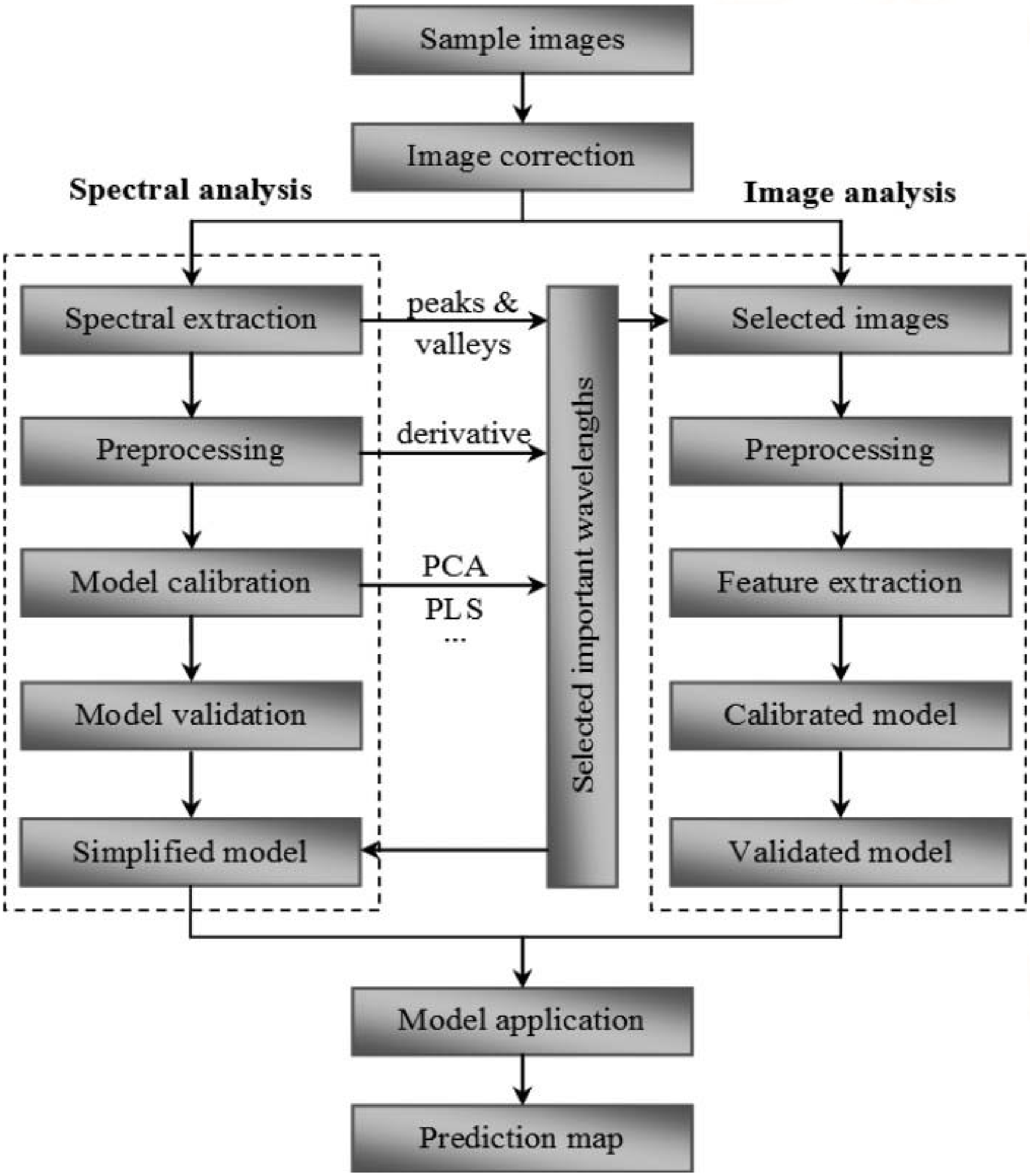


Figure 5: Flow chart of the routine for hyperspectral imaging processing.

Because of the special attributes of hypercubes, the analyses can be carried out in two alternative ways: either from perspective of spectral analysis or based on image processing. Nevertheless, appropriate data should be first prepared no matter which approach is selected. Before spectroscopic analysis, the spectra are first extracted from regions of interest (ROIs),which are mostly determined by thresholding an image at a single waveband or at a ratio and/or difference image. While, for image processing, limited number of images (preferably less than 10) should be chosen from the massive images available to facilitate fast computation. Usually, these images are those at important wavelengths, which require careful sifting. To do this, location of the bands where peaks and valleys occur in the original or preprocessed (mainly, first or second derivatives) spectra offers an option (Shao et al., 2011). To reach the same goal, chemometric methods, such as principal component analysis(PCA) and partial least square regression (PLSR), can be employed where the loadings and importance in projection (VIP)scores can be examined to find out vital wavelengths (ElMasry et al., 2008). Moreover, some other data compression methods(i.e., Fourier transform, singular value decomposition, and soon) can also enhance the capability of HSI for processing more images (Bonnier et al., 2008; Kulmyrzaev et al., 2008). After the data are available, the next task is to establish reliable calibrationmodels. However, before implementing chemometric algorithms, it is necessary to reduce the noise so as to enhance thesignal-to-noise ratio. For example, concerning spectral analysis, multiplicative signal correction and standard normal variation can help eliminate light scattering effect arising from physical properties of the samples (i.e., firmness, particle size, etc.),while derivative methods can either suppress baseline shifts ordered the spectra, so that more details within the spectra cane revealed. In addition, image processing, such as binning, filtering, and so on, can also enhance the quality of data. During model calibration, from the spectral analysis part, it follows the same routines as in spectroscopy, which is shown in Fig. 3.Therefore, it will not be discussed here in detail, and further details can be found elsewhere (Sun, 2009). However, it is worth mentioning that the models built based on whole wavebands should be simplified so that the speed of pixel-wise prediction on a new sample can be substantially accelerated. Such simplification indicates inclusion of only important wavelengths, which can be selected as aforementioned.

Application of hyperspectralimaging in food analysis

The potential of hyperspectral imaging has been successfully proved in the food industry. Although more studies are conducted in food quality analysis, the application of hyperspectralimaging in food safety inspection and control is increasing, which will be specifically discussed in the following sections.

Physical Contamination and Defects

Fecal contamination on food surface and the presence of foreign materials in food matrices are two main issues in foodphysical contamination. Meanwhile, the defects of food matrix are always indicators of unsuitability of food for consumption.

Fecal and Ingesta Contamination

Fecal and ingesta contamination can introduce pathogenic microorganisms both in fruits and vegetables and in meats, leading to possible occurrence of food safety incidents.

***Fecal Contamination on Fruits and Vegetables*.**

Fecal contamination on apples may result in introduction of pathogenic microorganisms (e.g., *Escherichia coli* O157:H7) into unpasteurized apple juice or cider, which is a potential health threat to the public (Cody et al., 1999). Therefore, they should be refused for further processing. Hyperspectral imaging offers absolution for this through non-destructive measurement of feceson apples.

Detection of Foreign Materials

The presence of foreign substances in food commodities should be eliminated because they are hazardous to consumers.

Yoon et al. (2006) investigated the feasibility of using hyperspectralimaging on detecting bone fragments in boneless chickenfillets, and found that all the bones inserted in the meat could be recognized in transmittance mode given that the fillets were examined on both sides, and reflectance analysis enabled elimination of false positives.

Fruit

Most of the products that have been studied with hyperspectral imaging are fruits, targeting apple, citrus, pear, peach, oranges, almond nut, blueberry, citrus, grape seed, grape skin, and strawberry. The majority of these studies were carried out in reflectance mode and in the VIS-NIR range (about 400–1,100 nm). Chilling defects, diseases and quality attributes of fruits including soluble solids content, mealiness, *etc*., were clarified. Besides, a few studies have been carried out on strawberries and grape seeds in the NIR range

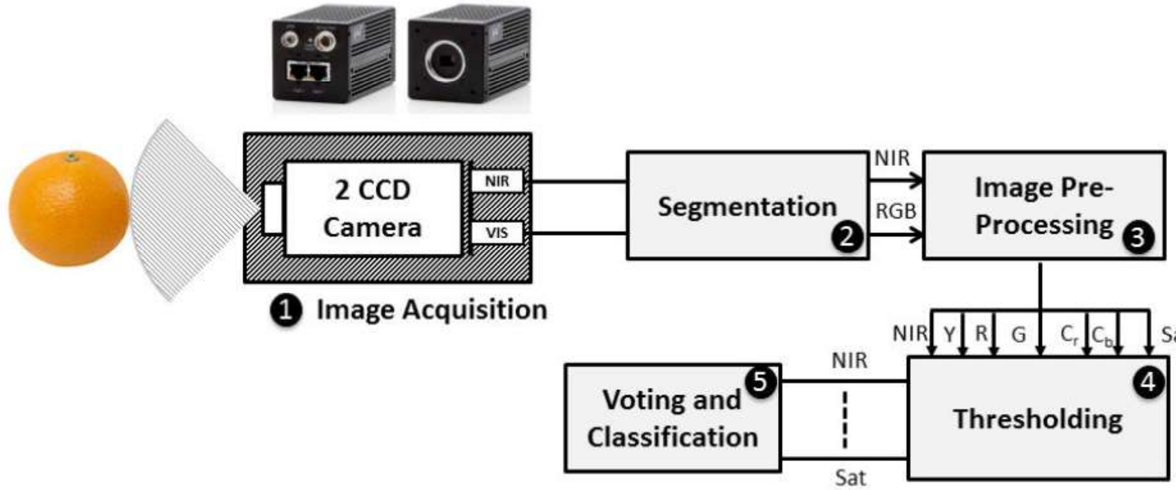


Fig. 6: The block diagram of the proposed orange fruit defects detection system

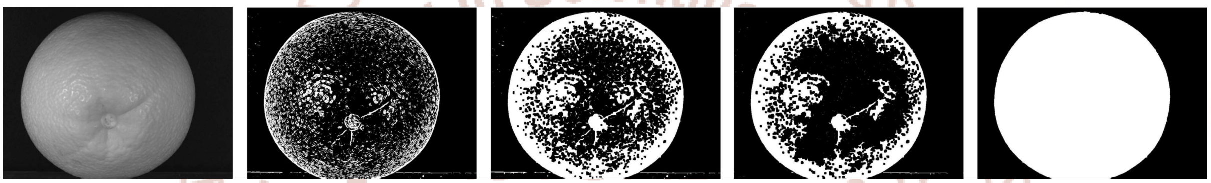


Fig. 3: Orange fruit Segmentation algorithm results. From left: NIR input image, Sobel edge detection, Morphological closing, Removing artifacts, Final mask

Vegetables

The main application of hyperspectral imaging on vegetables includes onions, mushrooms, pickling cucumbers and whole pickles, spinach leaves, and cherry tomato. The major adopted mode is still reflectance mode, while few studies were conducted in transmittance model and fluorescence modes. Ariana and Lu [93] developed a VIS-NIR hyperpsectral imaging system combining reflectance mode and transmission mode together, while using a moving transport platform. This system was applied to detect inner defected pickle pieces and classify pickling cucumbers and pickles, with spectral range of 500–1,000 nm. The system was capable of identifying inner defects of cucumber and pickles which were invisible to the naked eye.

Meat

Most meat researches related to hyperspectral detection were performed on pork, beef, and chicken fillet. Lamb [46] and ham [47,79] were also investigated. Liu *et al.* [41] applied a Gabor filter which is used in pattern recognition to preprocess hyperspectral images of pork. PCA was used to compress spectral features over the entire wavelengths (400–1,000 nm) into principal components (PCs). 'Hybrid' PCs were created by combining PCs from hyperspectral images with PC(s) from Gabor-filtered images. Both K-means clustering and LDA were applied to classify pork samples. The overall unbiased statistical classification accuracy reached 84 ± 1%. The comparison results of hyperspectral images and Gabor-filtered images based analysis proved that the texture features extracted by Gabor filter offered useful information for the differentiation of different levels of pork quality.

Seafood

Few studies on seafood have been reported in the last few years. The tested samples included fresh and smoked salmon, cod, prawn, and shell-free cooked clams. Considering the difficulties caused by shells, seafood holds promise as an attractive area for hyperspectral imaging research. The mostly studied object is salmon, whose fillet remains smooth and shell-free. Huang *et al*. [89] applied hyperspectral imaging on salmon's storage time prediction. PCA based *K*-means clustering and MLR were applied to relate hyperspectral data to the storage time and texture change of salmon, respectively. The result indicated that it is possible to predict the texture and storage time using hyperspectral imaging.

Biofilm Detection

Recently, Jun *et al.* [107] reported the utilization of macro-scale fluorescence hyperspectral imaging to evaluate the potential detection of pathogenic bacterial biofilm formations on five types of food-contact surface materials: stainless steel, high density polyethylene (HDPE), plastic laminate (Formica), and two variations of polished granite. These materials are commonly used to process and handle food, and sometimes cause biofilm pollution on food surface. Spots of biofilm (*E. coli* O157:H7 and *Salmonella* biofilm) growth were produced on sample surfaces and stored and scanned by fluorescence hyperspectral imaging system using ultraviolet-A excitation (421–700 nm, including a C-mount object lens, F1.9 35 mm).

Adulteration of Melamine

The safety-related food adulteration refers to the intentional addition of hazards into food. Among various examples, melamine is the most notorious due to the outbreak of milk powder scandal in China back in 2008 (Wu et al., 2009). The traditionalKjeldahl and Dumas method failed to detect melamine, because it only measures total nitrogen, which cannot reflect the content of melamine.

Microbiological Contamination

Currently, the detection of microorganisms in food relies heavily on culture and colony counting methods, which are commonly recognized as standard approaches. However, these techniques are destructive, laborious, and time-consuming. Instead, hyperspectral imaging has been explored for determination of microorganisms, including bacteria, fungi, and parasites, in a fast and precise way.

Bacterial Determination

Bacterial pathogens are the most confronted culprits for foodpoisoning caused by microbial hazards. Therefore, it is substantially important to know whether the meat to be eaten is still at acceptable level of bacterial loads or not, or whether undesired pathogens are present. Due to these concerns, on one hand, research for freshness/spoilage evaluation has been actively conducted, mainly focusing on meat and meat products. On the other hand, efforts have also been devoted to both qualify and quantify bacterial loads on a wide range of food matrices.

Fungal Contamination

Aflatoxin contaminated corns pose a serious threat to both humans and domestic animals because of mycotoxins, which are secondary metabolites that are toxic, immunosuppressant, and carcinogenic (Kalka et al., 2011; Yao et al., 2005). Therefore, relevant laws or regulations have been established to mandate the control of fungal contamination, especially on cerealproducts. Meanwhile, the cereal industry is also looking fornon-destructive, fast, and reliable methods for detecting fungalcontamination. Hyperspectral imaging was initially investigated in visible-near infrared bands to identify healthy wheatkernels from those with scabs (Delwiche and Kim, 2000).

CONCLUSIONS

This paper summarizes the application of hyperspectralimaging in food safety inspection and control. Hyperspectralimaging integrates two popular technologies, that is, spectroscopy and computer vision, to present both spectral and image information of food products at the same time. Such richness in information provides a broad platform for applying various chemometric algorithms and multivariate data analyses to reveal quality and safety parameters in the food commodities. Furthermore, this platform can be widened by introducing different spectral profiles, that is, NIR, Raman, and fluorescence spectra, and its effectiveness has been preliminarily confirmed in some aspects of food safety. However, as a promising technique, hyperspectralimaging should be expanded into more food safety fields to play a greater role in preventing outbreaks of food

safety problems.

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