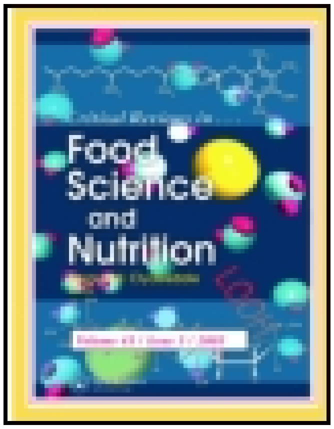

Critical Reviews in Food Science and Nutrition
Publication details, including instructions for authors and subscription information:
http://www.tandfonline.com/loi/bfsn20

Applications of Hyperspectral Imaging in Chicken Meat Safety and Quality Detection and Evaluation: A Review

Zhenjie Xiong [a], Anguo Xie [a], Da-Wen Sun [a b], Xin-an Zeng [a] & Dan Liu [a]
[a] College of Light Industry and Food Sciences, South China University of Technology, Guangzhou, P. R. China
[b] Food Refrigeration and Computerised Food Technology, University College Dublin, National University of Ireland, Agriculture and Food Science Centre, Belfield, Dublin 4, Ireland
Accepted author version posted online: 01 Apr 2014.

Applications of Hyperspectral Imaging in Chicken Meat Safety and Quality Detection and Evaluation： A Review

ZHENJIE XIONG[1], ANGUO XIE[1], DA-WEN SUN[1,2*], XIN-AN ZENG[1], DAN LIU[1]

[1]College of Light Industry and Food Sciences, South China University of Technology, Guangzhou, P. R. China

[2]Food Refrigeration and Computerised Food Technology, University College Dublin, National University of Ireland, Agriculture and Food Science Centre, Belfield, Dublin 4, Ireland

* Corresponding author. Tel: +353-1-7167342, Fax: +353-1-7167493, E-mail: dawen.sun@ucd.ie,
Website: www.ucd.ie/refrig; www.ucd.ie/sun.

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Abstract: *Currently, the issue of food safety and quality is a great public concern. In order to satisfy the demands of consumers and obtain superior food qualities, non-destructive and fast methods are required for quality evaluation. As one of these methods, hyperspectral imaging technique has emerged as a smart and promising analytical tool for quality evaluation purposes and has attracted much interest in non-destructive analysis of different food products. With the main advantage of combining both spectroscopy technique and imaging technique, hyperspectral imaging technique shows a convinced attitude to detect and evaluate chicken meat quality objectively. Moreover, developing a quality evaluation system based on hyperspectral imaging technology would bring economic benefits to the chicken meat industry. Therefore, in recent years, many studies have been conducted on using hyperspectral imaging technology for the safety and quality detection and evaluation of chicken meat. The aim of this review is thus to give a detailed overview about hyperspectral imaging and focus on the recently developed methods exerted in hyperspectral imaging technology developed for microbiological spoilage detection and quality classification of chicken meat. Moreover, the usefulness of hyperspectral imaging technique for detecting fecal contamination and bone fragments of chicken carcasses are presented. Finally, some viewpoints on its future research and applicability in the modern poultry industry are proposed.*

Keywords: Chicken, non-destructive methods, computer vision, hyperspectral imaging, near infrared spectroscopy

Introduction

As a global issue, food safety and quality receives increasing attention for both business and customers. People currently pay more attention to the safety and authenticity of meat. In China, chicken meat has always been considered as the most important poultry meat that provides protein, essential amino acids and a wide variety of micronutrients. The safety and quality of chicken meat is related to physical, chemical and biological conditions. Traditionally, the inspection processes are performed by human inspectors manually. However, in most cases these manual inspections are time-consuming and labour-intensive. Moreover, the accuracy of the tests cannot be guaranteed. Therefore, new techniques such as novel detection methods are continuously developed to enhance chicken meat safety and quality. In addition, development of effective quality inspection systems to ensure safe production of food during processing operations is one of the critical aspects for the food processing industry.

Non-contact optical techniques such as imaging and spectroscopy are currently available for food safety and quality inspection (Ariana and Lu, 2010; Barbin et al., 2012; Gowen et al., 2007; Shankar et al., 2010; Singh et al., 2010). Among them, imaging technique or computer vision has been used increasingly in the food industry for inspection and evaluation purposes as it can provide rapid and objective assessments (Barbin et al., 2013a; Chen et al., 2002; Du and Sun, 2004; Jackman et al., 2011; Pallottino et al., 2010; Sun, 2000). This technique is based on the analysis of spatial information acquired from the digital image of an object, which includes size and shape, color, surface texture and external defects, therefore image processing and analysis is the core of the technique with numerous algorithms and methods available to achieve the required classification and measurements. Due to its advantages mentioned above, computer vision has long been recognized as a promising technique for the objective assessment of meat quality (Brosnan and Sun, 2002). However, difficulties still exist. Normal computer vision operates at visible wavelengths in the forms of monochromatic or color images and is ineffective for classifying objects having similar colors. Even though external attributes such as size and shape, color, surface texture and external defects can be easily evaluated by computer vision, internal attributes (e.g., moisture, fat, and protein contents) are not possible to be detected with relatively simple and traditional imaging approaches because of very limited spectral information. On the other hand, spectroscopy technique is another well-developed optical technique for determining the essential properties of food products (ElMarsy and Sun, 2010; ElMasry et al., 2012a; Kamruzzaman et al., 2012a; Kamruzzaman et al., 2011). Recently, spectroscopy has gained a wide recognition for analyzing raw materials, product quality control, and process monitoring due to its rapidity, simplicity, safety as well as its ability to measure multiple attributes simultaneously. Although the spectroscopic technique is a reasonable compromise between simplicity and accuracy of predicting major composition of food produces, it is not able to provide some fundamental information, such as spatial distribution of quality parameters, which is essential to be demonstrated. The reason is that the measurement focuses only on a relatively small part of the sample being analyzed to produce average values of composition (Barbin et al., 2013b; Choudhary et al., 2009; Kamruzzaman et al., 2012b; Sone et al., 2012).

Thus, by combing the above two techniques, hyperspectral imaging (HSI), also known as “imaging spectroscopy or imaging spectrometry,” has emerged as a powerful technique for various quantitative applications in the food industry (Gowen et al., 2007; Kamruzzaman et al., 2013; Kang et al., 2011; Mizrach et al., 2009; Siripatrawan et al., 2011; Sun and Brosnan, 2003). Hyperspectral imaging technique can provides spatial information, as regular imaging systems, along with spectral information for each pixel within an image as spectroscopy. Because of the combined features, hyperspectral imaging technique can be used to detect physical and geometric characteristics such as size, shape, color and texture. It can also be used to extract some intrinsic chemical and molecular information (such as water, fat, protein, and other hydrogen-bonded constituent) from a product. Recently, this promising technique has been developed for quality assessment for various foods such as meat, fruit and vegetables (ElMasry et al., 2007; ElMasry et al., 2009; Li et al., 2011; Liu et al., 2007; Qiao et al., 2007; Rajkumar et al., 2012). Especially, in terms of applications in chicken meat analyses, hyperspectral imaging has been successfully applied to detect fecal contamination and wholesomeness of chicken carcasses (Casasent, 2008; Chao et al., 2010; Heitschmidt et al., 2004; Liu et al., 2003), to determinate skin tumors (Chao et al., 2011; Chao et al., 2007; Cho et al., 2007; ElMasry and

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Sun, 2010), as well as to detect microbial contamination (Feng et al., 2013; Feng and Sun, 2013a; Kumar and Mittal, 2010), as illustrated in Figure 1. Thus, this paper provides a detailed overview of the recently developed approaches and latest research efforts exerted in developing hyperspectral imaging technology for detecting and evaluating the safety and quality of chicken meat and the possibility of its widespread deployment.

Hyperspectral Imaging System

Fundamentals of Hyperspectral Imaging

Hyperspectral imaging is originally developed for remote sensing application utilizing satellite imaging data of the earth, moon, and planets, but has since found its application in other fields like agriculture, astronomy and medical diagnostics (ElMasry et al., 2012b; Taghizadeh et al., 2011). The common definition of hyperspectral imaging is the simultaneous acquisition of spatial images in many contiguous spectrum bands measured from a remotely operated platform. According to spectral resolution of sensors, spectral imaging technology can generally be divided into three categories called multispectral, hyperspectral, and ultraspectral (Feng and Sun, 2012; Valous et al., 2010; Zheng et al., 2006a). Multispectral imaging systems usually image the scene in just several spectral bands, and hyperspectral imaging systems are distinguished from multispectral imaging systems because hyperspectral imaging systems can acquire images in hundreds of spectral bands and have a much higher spectral resolution. For ultraspectral, it is typically used for spectral imaging systems with a very fine spectral resolution. Hyperspectral imager as the core component of the technology, is made up of imaging spectrometer and CCD (charge-coupled device) detector. The spectrum and image information of measured objects can be fast and efficiently obtained with it. When acquiring sample images, the imager receives light reflecting or transmitting from surface of the sample. Due to continuous movement of the sample, a sequential one-dimensional image as well as spectral information can then be obtained and all data are collected by a computer. Combining all narrow-band images with the spectral information, the spectral image of the entire sample can be finally acquired (ElMasry et al., 2013; Wang et al., 2012).

Hyperspectral imaging systems can obtain narrow and continuous spectrum data in visible (300-800 nm), visible and near infrared (400-1000 nm), short-wave near infrared (900-1700 nm) and long-wave near infrared (1000-2500 nm) regions, and then provide tens to hundreds of narrow band spectral information for each pixel. Finally, a complete and continuous spectrum curve can be produced. In terms of hyperspectral image generation, there are three fundamental ways known as tunable filter, pushbroom, and whiskbroom (Feng and Sun, 2012; Zheng et al., 2006b). These descriptive names refer to the hardware methodology used to acquire the data stream. Tunable filter depends on keeping the sample fixed, and obtaining imaging one wavelength after another and it is only practical if the number of wavelengths needed is limited as in multispectral imaging techniques. The other two ways depend on scanning the specimen in

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the spatial domain by moving the specimen either line-by-line (pushbroom) or point-by-point (whiskbroom), respectively. The great advantage of a whiskbroom scanning is that the light for every spatial element passes through the same path of the optical system and it is commonly used for microscopic imaging where the acquisition time is usually not a problem. Nevertheless, among these three scanning approaches, pushbroom imaging is the most popular one in the food industry due to its speed and versatility.

Hyperspectral imaging techniques are commonly implemented in one of three modes: reflectance, transmission, and fluorescence (Feng and Sun, 2012; Zheng et al., 2006a; 2006b). While the majority of published research on hyperspectral imaging has been performed in reflectance mode (Lu and Chen, 1999; Mahesh et al., 2008; Mehl et al., 2004; Naganathan et al., 2008), transmission and fluorescence modes have also been investigated (Kim et al., 2005). The principle of reflectance is that the light reflected by the illuminated specimen is captured by the detector in a specific conformation. It is usually applied for particulate materials in the wavelength range from 400 to 1000 nm or 1000 to 1700 nm and has been used to detect defects, contaminants and quality attributes of meat products. Transmission hyperspectral imaging is potentially applicable for the online estimation of internal constituent concentrations and detection of internal defects in foods. Transmission is more commonly measured from 800 to 1100 nm or 700-900 nm. The amount of light transmitted through the substance is often very small but carries more valuable information and the detector is positioned on the opposite side of the light source to acquire the image. Different from transmission, fluorescence spectroscopy is well established as an analytical technique for food control, especially in the dairy industry. Some chemical components, such as chlorophyll, excited by UV light generally emit in the visible-near infrared region. Hyperspectral fluorescence imaging is emerging as a tool for food quality investigation (Lefcourt et al., 2005).

Components of Hyperspectral Imaging System

Although the three hyperspectral imaging systems described above are very common in a wide variety of applications, pushbroom acquisition mode is the most common method currently implemented in recent research work in meat quality evaluation. A typical pushbroom hyperspectral imaging system consists of the following components: an imaging spectrograph coupled with C-mount lens, a high-resolution CCD or CMOS (complementary metal oxide semiconductor) camera, an illumination unit, a sample transportation plate controlled by a step motor and a computer equipped with image acquisition software. The camera, spectrograph and illumination conditions determine the spectral range of the system. The camera is a two-dimensional detector (CCD or CMOS) to simultaneously collect the spectral and spatial information, and the spectrograph is the most important part of the system, which helps in generating a spectrum for each point on the scanned line. The sample is usually diffusely illuminated by a halogen source. A line of light reflected from the sample enters the objective

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lens and is separated into its component wavelengths by diffraction optics contained in the spectrograph. Then, a two-dimensional image (spatial dimension × wavelength dimension) is formed on the camera. Since the camera captures only a line of the illuminated object, the sample is moved past the objective lens on a motorized transactional stage so that the entire surface of the specimen can be scanned. Two dimensional line images acquired at adjacent points on the object are stacked to form a 3-D hypercube, which may be saved on a computer for further analysis. The schematic representation of the main configuration of a pushbroom hyperspectral imaging system is shown in Figure. 2.

Image Acquisition and Data Structure

During image acquisition, each sample is put on the translation stage and conveyed to the field of view (FOV) of the camera. The entire image acquisition process is controlled by a computer. When a sample comes into the FOV, a hyperspectral image is acquired and the image is sent to the computer for storage in a raw format before processed. Each hyperspectral image is made up of hundreds of contiguous wavebands for each spatial position of a sample studied. For this reason, each pixel in a hyperspectral image contains the spectrum of that specific position. The resulting spectrum acts like a fingerprint, which can be utilized to characterize the composition of that particular pixel. Hyperspectral images, called hypercubes, are a three-dimensional (3-D) block of data with two dimensions being spatial and the third spectral (Nagata et al., 2006).

Figure 3 demonstrates schematic representation of hyperspectral imaging hypercube showing the relationship between spectral and spatial dimensions. A hyperspectral image can be represented by a 3-D cube of images I (x, y, λ_i), where indices x = 0, 1, …, N-1, y = 0, 1, …, M-1 are spatial coordinates and λ_i, i= 0, 1, …, L-1 denotes the spectral band. For a fixed λ_k, I(x, y, λ_k) represents the k^{th} single-band image. If x and y are fixed, then I(x, y, λ_i) stands for the spectrum or spectral information. As hyperspectral imaging combines the technologies of conventional imaging and spectroscopy, this combined nature of imaging and spectroscopy enables the system to simultaneously provide physical and geometrical features of the product (i.e., shape, size, appearance, and color) as well as the chemical composition of the product through spectral analysis. Therefore, hyperspectral imaging technology has the unique advantages in detecting external or internal quality of meat product.

Image Processing

Due to the imperfections of the systems, the images acquired are subject to various distortions. Therefore, subsequent image processing plays an important role in obtaining better images. Typically, image processing task involves four major steps including image correction, segmentation, regions of interests (ROIs) identification, and feature extraction. Firstly, to overcome the problem of the spectral non-uniformity of the illumination and influence of the dark current, the images need to be calibrated with a white and a dark references (Burger and

Gowen, 2011). Generally, a dark image (with 0% reflectance) is obtained when the light source is turned off and the camera lens is completely covered with its opaque cap. Furthermore, a white reference image (with 99% reflectance) is obtained by acquiring a spectral image from a uniform, high reflectance white calibration tile. The corrected image (R) is calculated using the following equation:

$$R = \frac{I - I_d}{I_w - I_d} \tag{1}$$

where R is the corrected spectral image of the sample, I is the original spectral image of the sample, I_d is the dark reference image, and I_w is the white reference image. The corrected images will then be the basis for subsequent image analysis to extract usual information of each sample as well as selection of effective wavelengths. In addition, some other processing methods such as histogram equalization, filtering, transformation and arithmetic operation are properly used to obtain further improved images. Secondly, image segmentation is another essential step in image processing as subsequent extracted data are highly dependent on the precision of this operation. The main intention of segmentation is to isolate only the meat sample portion in the image and avoid any undesired information from the background as well as the sample holder. The elimination of the background is often performed by a masking operation that converts the background pixels to zero reflectance. Thirdly, regions of interests (ROIs) are identified in the tested objects, which are used for extracting useful information pertaining to the desired features. The effect of segmentation makes an important influence on identifying ROIs. Finally, useful information of desired features can be extracted by deciphering image data after the ROIs are successfully identified. In general, images are stored and processed in the form of matrices by pixels. On one hand, the location of pixels in images can provide geometric information of the object, such as size and shape. On the other hand, the pixel intensity value can be used to extract the surface information of the objects, including color and texture. At this stage, different operations are usually carried out to extract further information from the image or to highlight the variation among different regions of the image. For example, textural analysis by gray level co-occurrence matrix and Gabor transform are two widely used algorithms of hyperspectral image processing (ElMasry et al., 2013). Moreover, the generation of chemical images in a pixel-wise manner is an important way of hyperspectral image processing. These chemical images are created to visualize quantitative spatial distribution of meat sample components and their relative concentrations (ElMarsy and Sun, 2010).

Spectral Pre-processing

The purpose of spectral processing is to improve the quality of instrumental measurements as well as to reduce or eradicate information, which is present in the spectra but has little correlation with the target values to be modeled. There are three common preprocessing methods called derivate, multiplicative scatter correction (MSC), and standard normalized variate (SNV). Derivative methods can remove effects of baseline offsets or slops and also facilitate distinguishing overlapped spectral peaks. Moreover, derivate methods are powerful to eliminate background noise in order to enhance spectral resolution. Considering that derivative methods are prone to exaggeration of noise, original spectral images are required to have a higher signal-to-noise ratio. SNV and MSC are both able to correct multiplicative noise arising from the physical structure of specimens. To apply multiplicative scatter correction, a reference spectrum is needed, which is calculated as the average of the mean spectra for each image (a sample). MSC shows that each spectrum approximately has a linear relationship with the mean spectrum in a calibration set. Therefore, a linear relationship exists between the spectrum and the average spectrum of each sample. The size of additional effect (intercept) reflects the unique reflection effect of samples while the size of the slope reflects the uniformity. Through correction, the stochastic variation is deduced as much as possible. In the case of better linear relationship between spectrum and concentration or similar chemical properties, MSC have a better correction. SNV transformation is performed based on individual spectrum, which requires the calculation of the mean and standard deviation (SD) values of the specific spectrum. The capability of SNC in correction is better than that of MSC, especially when components of samples change greatly. Generally, SNV is considered to be an outstanding method in near-infrared spectral image processing. Finally, all the above pre-processing methods can be implemented in specilised software such as Matlab (The Mathworks Inc., Natick, MA, USA).

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Data Processing

Hyperspectral imaging systems usually have a high spectral resolution, and the acquired spectral data often contain hundreds of wavelength bands. The large amount of data could make data processing difficult. Therefore, spectral dimension reduction and uninformative wavelength elimination need to be conducted to speed up the subsequent data processing and improve prediction results in terms of accuracy and robustness. Currently, methods for dimensionality reduction include principal component analysis (PCA), independent component analysis (ICA), and genetic algorithm (GA). The final purpose is to establish a corresponding discrimination model, with methods of multi-linear regression (MLR), partial least squares (PLS) as well as artificial neural networks (ANN). However, developing a proper calibration model is always a difficult task. If a satisfactory model is established, its application can become easy and fast, which enables hyperspectral imaging system to meet the requirements for rapid and non-destructive inspections in the food industry.

PCA is not only a very effective data reduction technique for spectroscopic data but also the most frequently used unsupervised classification technique. PCA summarises data by forming new variables, which are linear composites of the original variables. The new variables (principal components) are uncorrelated and represent the most common variations to all the data. The score is the estimated value for a principal component. Each spectrum has a score along each principal component. ICA is the expansion of PCA, which seeks non-singular transformation of multivariate data in order to keep data components after conversion as independent of each other as possible. In the implementation of algorithms, ICA is different from PCA, which only considers second-order statistics of input data. As ICA efficiently uses higher-order statistics of input data, it can better reflect the essential characteristics of the input data. Moreover, compared with PCA that is a standardized algorithm, ICA is feasible to utilize different objective functions, resulting in different results.

PLS, developed from principal component regression, is a method for constructing predicting models when the factors are many and highly collinear. The general idea of PLS is to try to extract latent (not directly observed or measured) factors, accounting for as much of the manifest factor variation as possible while modeling the responses well. In detail, PLS is based on the spectral decomposition of X and Y, where X is the matrix of factor values and Y is the matrix of response values. The extracted factors from X and Y, also referred to as X-scores and Y-scores respectively, are both chosen so that the relationship between successive pairs of scores is as strong as possible. This is like a robust form of redundancy analysis, seeking directions in the factor space that are associated with high variation in the responses but biasing them toward directions that are accurately predicted. The aim of MLR is to establish a relationship between the response variable and observed spectral variables, by the way of fitting

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a linear equation to the observed data. The regression coefficients between the predicted and observed response values in a least squares sense are calculated by minimizing the error. MLR models typically do not perform well due to high co-linearity of the spectra and easy loss of robustness of the calibration models. ANN is a mathematical model or computational model that is inspired by the structure and/or functional aspects of biological neural networks. Modern neural networks are modeling tools for non-linear statistical data. They are usually used to model complex relationships between inputs and outputs or to find patterns in data. ANN has been demonstrated to be effective in identification and classification of agricultural products (ElMasry et al., 2009; Goodacre et al., 1998; Siripatrawan et al., 2011), where non-coherence or non-linearity often exists. A dimensionality reduction technique is performed to remove redundant information from the hyperspectral image, thus creating simplified data. Therefore, various data analysis methodologies comprising of computer programs and algorithms are required to analyze hyperspectral images and then to generate data that describe material properties of the tested samples.

Recent Applications in Chicken Safety and Quality Evaluation

In recent years, hyperspectral imaging technique has been extensively implemented for safety and quality evaluation and monitoring of chicken meat and chicken carcasses (Chao et al., 2002; Du et al., 2007; Fletcher and Kong, 2003; Kong et al., 2004; Liu and Chen, 2001; Liu et al., 2003; Nakariyakul and Casasent, 2004). The principle of hyperspectral imaging technique for detecting chicken quality is described as follows. Different chemical compositions and physical characteristics of food have different reflectance, dispersion, absorption and electromagnetic energy at a specific wavelength. Critical peaks at different wavelengths can indicate material attributes (spectral fingerprint) of different compounds in order to achieve qualitative or quantitative detection of food quality by spectral signal analysis. According to information of spatial distribution provided by hyperspectral image, visualized expression of quality information, quality classification and detection can all be realized. Application of hyperspectral imaging for quality assessment of chicken and chicken products are mainly concentrated on the differentiation between wholesome and unwholesome freshly slaughtered chickens, chicken quality classification, and detection of contaminants and tumors in chicken carcasses. It is believed that a suitable system for objective analysis of chicken quality would improve the ability to market chicken on value and to monitor and manage the wholesomeness of chicken in the supply chain. In fact, some developed hyperspectral imaging systems have already been implemented in a real-time inspection line where spectral image is captured for each chicken, and then the image is processed by analysis software in computer to determine whether if the chicken has a contaminant or disease (Kim et al., 2010a; Kim et al., 2010b; Yoon et al., 2010). In addition, defects in chicken also include bruises, air sacculitis, inflammation, ascites and leukosis. These defects can undergo a fast deterioration process, thus pose great threat to human health. To ensure superior chicken quality free from hazards, deterioration or contamination, each contaminant needs to be identified and classified. Spectral diagnostic systems can be used as a non-invasive tool to monitor the production line of chicken carcasses at all stages of production by spectral profiles from hyperspectral image. After developing, calibrating, validating, and testing the hyperspectral imaging system, a multispectral imaging system can then be generated with limited effective wavebands for certain application in a real-time implementation. In this case, such a system can play an important role in inspecting a huge number of chickens in real harsh working environment. Table 1 summarizes different applications of hyperspectral imaging for safety and quality detection of chicken meats.

Microbiological Spoilage Detection

It is well-known that all chicken meat supplied to the markets must undergo quality controls in order to guarantee consumer safety. If storage conditions are improper, undesirable microorganisms may grow, which affects product safety and quality. These bacteria can lead to sensory changes, discoloration, and changes in taste (Wu and Sun, 2013). Currently, for detection and enumeration of spoilage bacteria, there are over 40 methods available, including enumeration methods based on microscopy, ATP (adenosine triphosphate) bioluminescence, and the measurement of electrical phenomena, as well as detection methods based on immunological, nucleic acid-based procedures, and molecular approaches. The above-mentioned traditional methods are time-consuming, labor-intensive, which cannot satisfy the requirement of industrial production and meet the needs of domestic consumption and export trade. In addition, these methods give only retrospective information about the sample analyzed. In order to overcome these shortcomings, there is a need for advanced technology that can provide rapid, accurate and non-destructive detection of bacterial spoilage or contamination in fresh chicken meat. Therefore, hyperspectral imaging technique has been proposed. Recently, several studies have shown that hyperspectral imaging system in visible and near infrared range (400-1100 nm), in combination with other analysis methods, was able to detect the bacterial spoilage in chicken meat (Feng and Sun, 2013a; Feng et al., 2013; Feng and Sun, 2013b).

Feng and Sun (2013a) investigated the potential of using near infrared hyperspectral imaging and different spectroscopic transforms to detect the total viable count (TVC) of bacteria in raw chicken fillets. In their study, after the hyperspectral reflectance images were acquired and corrected, stepwise regression was then used to select the optimal wavelengths that could characterize the gross change of TVC on chicken meat. At the meantime, the resulting reflectance images were transformed into hypercubes in absorbance and Kubelka-Munck (K-M) units. Three partial least squares regression (PLSR) models were established based on reflectance spectra, absorbance data and K-M parameters, called RS-PLSR, AS-PLSR and KMS-PLSR, respectively. The results showed that the KMS-PLSR model was the most optimal, which resulted in high correlation coefficients (R) of 0.96 and 0.94 as well as low root mean squared errors (RMSEs) of 0.40 and 0.50 log10 CFU per gram for calibration and cross validation, respectively. This research demonstrated the feasibility of using near-infrared hyperspectral imaging (910-1700 nm) as a valid means for non-destructive determination of total viable counts in chicken fillet samples. In terms of detecting specific bacteria, Feng et al. (2013) used the hyperspectral imaging technique as a non-destructive tool for quantitative and direct determination of *Enterobacteriaceae* loads on chicken fillet. Only three wavelengths (930, 1121 and 1345 nm) were selected but more preferred for predicting *Enterobacteriaceae* loads with R^2 of 0.87 and RMSEs of 0.45 log 10 CFU per gram for prediction. Moreover, Feng and Sun (2013b) used near-infrared hyperspectral imaging in tandem with partial least squares regression and genetic algorithm for non-destructive determination and visualization of *Pseudomonas* loads in chicken fillets. The best model utilized 14 bands in five segments and produced R and RMSEs of 0.88 and 0.64 log log10 CFU per gram for prediction. All the above three studies had the advantage of constructing a prediction map providing the distribution of bacteria on chicken fillet, which cannot be achieved by conventional methods.

Chicken Quality Classification

Procedure for quality classification of chicken on slaughtering line represents an important step in chicken meat production and accurate chicken classification is important for its pricing, authentication, and grouping to meet special requirements of consumers. Usually, chicken meat grading is carried out by experienced human inspector according to grading standards or by some chemical techniques. However, these traditional methods with weaknesses of time-consuming and destructive manner are not suitable for rapid inspection. Accordingly, the chicken industry seeks non-destructive, rapid and efficient methods for fast classification of chicken meat, leading to great interest in using hyperspectral imaging technique. The principle of hyperspectral imaging technique for chicken meat quality classification is to build calibration models using spectral signatures of known quality grades, and then use these models to predict the quality class of unknown samples. Once an optimal model is established, it can be used for commercial production, which will help producers to correctly sort chicken according to quality grades, to screen or eliminate lower quality chicken before processing or packaging, and to price higher quality chicken appropriately. Systemically diseased chicken refer to the chicken infected with septicemia/toxemia or those with inflammation, where pathogenic bacterium and toxic wastes as well as inadequate absorption of yolk sac are to be blamed. Septicemia results from the invasion of pathogenic microorganisms, which could release toxins in the bloodstream, and toxemia is caused by toxins produced by cells at a localized infection or from the growth of microorganisms. Because inspection regulations require ideally zero tolerance for unwholesome chickens exhibiting symptoms of septicemia or toxemia, these abnormalities are mandated to be

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isolated from the normal chicken and thus must be completely removed from processing lines. To achieve this goal, hyperspectral imaging system was successfully used to differentiate freshly slaughtered chickens from diseased chickens (Yang et al., 2005a; Yang et al., 2005b; Yang et al., 2006).

Lu and Chen (1999) obtained hyperspectral images from four classes of poultry carcasses (normal, cadaver, septicemia, and tumor) and observed differences in the spectra of the relative reflectance between wholesome and unwholesome carcasses. Their conclusion was that the discrepancies within spectra of 675 wholesome and systemically diseased chickens were prominent at feature wavelengths. Moreover, differences among the three classes of unwholesome carcasses from their respective spectra were obvious. This fact provided the basis for the identification of unwholesome from wholesome chicken. Chao et al. (2007) developed an hyperspectral-multispectral line-scan imaging system for automate poultry carcass inspection on a commercial evisceration line moving at a speed of 70 birds per minute and achieved 97.6% accuracy for wholesome birds and 96.0% accuracy for systemically diseased birds in the testing dataset. In another study (Chao et al., 2008), an online line-scan imaging system was developed and tested on an eviscerating line at a poultry processing plant with 140 birds per minute for differentiation between wholesome and unwholesome chickens, resulting in correct identification equivalent to that by human inspectors. This imaging system (Chao et al., 2008) was tested with about 100,000 chickens on a commercial line and achieved over 99%

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accuracy in identifying unwholesome chickens. Chao et al. (2008) emphasized that their study should stimulate more research works in this field to produce more efficient and comparable systems in different directions of chicken quality and control programs, which can help poultry plants to improve their production efficiency, satisfying increasing consumer demand for poultry products.

Contamination Detection in Chicken

Surprisingly, contamination is rather common on chicken products. A typical large chicken processing plant may slaughter over a million birds every week. During slaughter and processing, intestinal contents can spill onto machinery, leading to the contamination of chicken muscles and organs. Feces are the source of many types of pathogenic organisms, including parasites (Lawrence et al., 2003; Lawrence et al., 2004; Lefcourt et al., 2005; Nakariyakul and Casasent, 2007). Therefore, fecal and ingesta contaminants on poultry carcasses are prohibited as they can lead to possible occurrence of food safety incidents. Microbial pathogens can be transmitted to humans by consumption of contaminated undercooked or mishandled poultry meat. Thus, reduction of the potential health risk to consumers caused by such food-borne infections is a very important food safety issue and public concern. The inspection process currently employed for contamination in poultry carcasses is usually conducted by human visual observation where trained human inspectors carry out the inspection and examine a small

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number of representative samples from a large production run. In general, fecal material color ranges from varying shades of yellow to green, brown, and white; the consistency of feces is usually semi-solid to past; and the composition of feces may include plant material (Nakariyakul and Casasent, 2008; Nakariyakul et al., 2007). Inspectors use guidelines to verify that establishments prevent poultry carcasses with visible fecal contamination from entering the chilling tanks. However, this manual method is both labor intensive and prone to both human error and inspector-to-inspector variation (Park and Chen, 2001; Park et al., 2007a; Windham et al., 2005a). Compounding these challenges, there are requirements to identify contaminants at commercial processing speed in harsh environments. As hyperspectral imaging is a useful tool to analyze the spectra of an object that contain contiguous spectral and spatial information, it can thus be an effective technique for identifying surface contaminants on poultry carcasses.

In the area of contamination detection that is frequently required on the surfaces of poultry carcasses, researchers at United States Department of Agriculture (USDA) have developed hyperspectral imaging systems with different designs and sensitivities for the identification of fecal matter and ingesta. Their preliminary results have demonstrated that the spectral imaging technique can be used effectively for detecting fecal spots on contaminated carcasses in the visible/near-infrared (NIR) spectral region. Their later inspection system has resulted in lower rates of disease and faecal contamination on poultry and been installed in an on-line inspection system where chickens having diseases, contaminations, or defects are identified in real-time.

This later inspection system showed good performance in harsh working environment for inspecting a huge number of chickens. In addition, intensive research has been exerted by the USDA Agricultural Research Service (ARS) for calibrating the hyperspectral imaging systems, identifying spectral signatures of different contaminants in the visible and near-infrared regions, developing algorithms for fecal detection, and spectral image processing and exploiting the system in on-line multispectral applications (Park et al., 2002; Park et al., 2006; Windham et al., 2005b).

The detailed steps of detecting different fecal contaminants (feces and ingesta) in poultry carcasses are summarized by Park et al. (2002). Spectra of homogenous samples of feces, ingesta, and skin were first collected either by using VIS/NIR spectrometer or from the hyperspectral image itself. Then those spectra were evaluated with PCA to reduce the dimensionality of the hyperspectral data. Also, optimum wavelengths (434, 517, 565, and 628 nm) were identified for further analysis by the highest value of PCA loadings and calibration regression coefficients. Hyperspectral data were then collected on contaminated poultry carcasses and information learned from the spectroscopic data was used to aid in hyperspectral data analysis. Finally, the results of the hyperspectral data were used to identify a few optimum wavelengths for use in a real-time multispectral imaging system. By testing different combinations of band ratios between these wavelengths, band ratio of dual-wavelength (565/517) images followed by histogram stretching was effective in the identification of fecal and ingesta contamination of poultry carcasses. Test results indicated that the detection accuracy was 97.3% for linear and 100% for non-linear histogram stretching. Figure 4 shows visual results of a poultry carcass with the image-processing algorithm applied to a calibrated smoothed pre-processed hyperspectral image (Park et al., 2006). As shown in Fig. 4c, there was an obvious difference in contrast between normal skin of the carcass and the contaminant, which could be easily detected by using various threshold values as shown in Fig. 4e. In another research (Park et al., 2007b), spectral angle mapper (SAM) supervised classification method for hyperspectral poultry imagery was performed for classifying faecal and ingesta contaminants on the surface of the broiler carcasses (Park et al., 2007b). Based on the comparison with ground truth region of interest, both classification accuracy and kappa coefficient, which quantifies the agreement of classification, increased when spectral angle increased. The overall mean accuracy and corresponding mean kappa coefficient to classify faecal and ingesta contaminants were 90.13% and 0.8841 when a spectral angle of 0.3 radians was used as a threshold. In addition to the spectral angle mapperalgorithm, Park et al. (2007c) used fisher linear discriminant analysis (FLDA) for improving fecal detection accuracy with hyperspectral images, achieving 98.9% detection accuracy and 1.1% omission error.

In contaminant detection of poultry using hyperspectral imaging technique, the USDA research team (Lawrence et al., 2003; Park et al., 2006; Park et al., 2007c; Windham et al., 2003) had also developed some useful algorithms for enhancing detection accuracy. In their earlier

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studies, Windham et al. (2003) validated the 567nm/517nm quotient to classify uncontaminated skin from feces/ingesta and investigated the use of single-term linear regression (STLR) to select key wavelengths (434, 517, 565, and 628 nm) for classification. Their optimized method based on STLR was able to classified 100% of contaminants with no false positives. By using another approach, Windham et al. (2005) determined the effectiveness of hyperspectral imaging for detecting ingesta contamination spots varying in mass from the crop and gizzard. They applied a decision tree classifier algorithm to the images at wavelengths of 517, 565, and 802 nm, producing a Boolean output image with gizzard and crop contaminates identified. The imaging system identified 100% of the 10, 50, and 100 mg gizzard and crop content contaminants applied on the carcasses. However, not every pixel associated with a given spot (contaminant ground truth) was detected. As proved from these studies, the detection of contaminants depends on the largest difference in spectral difference between contaminants and normal skin. Also, the wavelengths at which the contaminants gave the highest contrast with the normal skin would act as optimal wavelengths for this purpose. On the other hand, in terms of studies on expatiating washing effect, Lawrence et al. (2006) designed an experiment where two washing times as well as two exposure times were included, and the result explained that with longer exposure time, more fecal strains could be detected, while washing time did not obviously influence the classification. However, strains were not viewed as hazards, therefore, their identification would turn out to be false positive for fecal detection systems. To avoid this, Lawrence et al. (2006) suggested the addition of a third wavelength. Detection results all demonstrated the effectiveness of these systems for identifying feces on poultry surfaces in spite of the harsh environment involved. Furthermore, in more recent studies of in-plant real-time detection, it was found that their hyperspectral imaging system was able to identify successfully fecal spots on the carcasses at a high-speed processing line (140 birds per minute), and the detectable feces could be as little as 10 mg (Park et al., 2010; Park et al., 2011).

Tumor Detection in Chicken

Unwholesomeness of chicken also includes the symptom of tumors, and thickened skin areas usually with ulcerous lesions in the middle. Skin cancer causes skin cells to lose the ability to divide and grow normally, and induces abnormal cells to grow out of control to form tumors. Tumors are not as visually obvious as other pathological diseases such as septicemia, air sacculitis, and bruise since its spatial signature appears as shape distortion rather than a discoloration. Therefore, their detection is a big challenge because most of these blemishes are rather difficult to discern by using traditional manual inspection. In this aspect, hyperspectral imagery shows great potential for detection and classification of biomedical abnormalities because it provides both spatial and spectral features about the objects of interest in the image. Currently, two methods are popular including hyperspectral fluorescence imaging and hyperspectral reflectance imaging. However, hyperspectral imaging technique in tumor detection is not perfect because tumors have different spectral responses and some parts of normal chicken skin can even have similar spectral response to that of tumors, making the identification of tumors a difficult task (Nakariyakul and Casasent, 2004).

Fluorescence imaging is an alternative technique in which a number of compounds emit fluorescence in the visible region of spectrum when excited with UV radiation. Exogenous contaminants as well as intrinsic changes in food products due to anomalies may contribute to changes in the fluorescence of food commodities (Kim et al., 2001). Recently, some research endeavors using the hyperspectral fluorescence imaging technique have been accomplished for detecting chicken skin tumor (Du et al., 2007; Fletcher and Kong, 2003; Kim et al., 2004; Kong, 2003; Kong et al., 2004). In their experiment for detecting tumors in chicken carcasses, Kim et al. (2004) presented a method using hyperspectral fluorescence imaging system, but they failed to detect tumors that were smaller than 3 mm in diameter. Their resultant detection rate, false positive rate and missing rate were 76%, 28%, and 24%, respectively. In another work, Kong et al. (2004) presented a hyperspectral fluorescence imaging system with a fuzzy inference scheme for detecting skin tumors with a detection rate of 82%. The computational speed of tumor detection can be accelerated by using only several optimal wavebands selected from hyperspectral data to identify a subset of significant spectral bands in terms of information content and to remove the bands that were less important. Working in this, classification accuracy of 96% and 90.6% were obtained using support vector machine (SVM) with features selected by PCA and recursive divergence, respectively (Du et al., 2007; Fletcher and Kong, 2003), which were higher than those described above. With the development of fluorescence techniques and with the help of other analytical methods (such as probabilistic neural network), high tumor detection rate of up to 98.2% was achieved (Park et al., 2006).

Reflectance imaging technology is the other hyperspectral imaging detection technology used for tumor detection. Chao et al. (2000) applied PCA on the hypercubes and found tumors appeared in the blue and green bands. By using the ratio of three bands, a feature image was created. After that, they calculated four statistical moments (later translated into three features) as inputs for a fuzzy interference system. Chao et al. (2000) finally found the optimal and satisfactory classification with fuzzy rules based on the values of features. Later, more feature wavelength selection methods such as modified and adaptive branch and bound (MBB and ABB) were applied to enhance the accuracy (Nakariyakul and Casasent, 2007; 2009). Other feature selection methods including discrete wavelet transform (DWT), and kernel discriminant analysis (KDA) were applied by Xu et al. (2007) to extract the independent feature sets from hyperspectral reflectance image (425–711 nm) and then classified each feature individually by a linear classifier. The results demonstrated that better performance was obtained in detecting skin tumor when using combining classifiers as compared to single classifier.

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Detecting Bone Fragments

Consumers expect food products to be free from biological, chemical, and physical contaminants. Fragments of bone in boneless poultry meat are significant hazards to consumers and also a problem for the industry, whether in processed products or high quality breast meat. Bone fragments may occur due to misaligned cutting blades shaving pieces from the skeleton, or they may be due to bones that were already broken before or during slaughter. Bone fragments such as clavicle (wishbone), which is a long, sharp and completely calcified bone, have the potential to cause injury. Because of bone fragments, breast meat is trimmed off and assigned to cheaper products during production process. Moreover, commercial poultry processors lose customers and spend considerable resources each year for insurance claims and legal fees due to broken bones found in de-boned chicken meat. Hence, there is a need to detect and remove these physical hazards from deboned chicken products before marketing. Yoon et al. (2007; 2008) employed both transmittance and reflectance hyperspectral imaging, which is a non-ionized and non-destructive imaging modality, to detect bone fragments in de-boned chicken fillets. In order to reduce the influence of light scattering on images and thus increase the image contrast, Yoon et al. (2007) utilized a back-illuminated structured light source in a transmittance mode to exploit imaging patterns characteristic of embedded bones. Then, Yoon et al. (2008) proposed an enhancement technology using an illumination-transmittance model for correcting non-uniform illumination effects so that embedded bones were more easily detected by a simple segmentation method using a single threshold value. Their results were promising, showing that the hyperspectral imaging system was effective for detecting bones on poultry carcasses when combining with appropriate image processing algorithms.

Future Trends

Nowadays, hyperspectral imaging technique as a fast, accurate and non-destructive method has been applied in chicken meat safety and quality detection, showing that hyperspectral imaging technique will have a board application prospect on chicken meat detection and evaluation in future research. However, the accuracy of quantitative analysis on chicken meat quality is still insufficient, although qualitative analysis has made good progress by using hyperspectral imaging technique. The way of solving this problem is to increase the accuracy of spectrum devices and to reduce the interference of useless information. As a combination of spectroscopy and traditional imaging, hyperspectral imaging technique can obtain both spatial and spectral information from chicken meat samples simultaneously. Accordingly, the issue of high dimensionality of hyperspectral data is a challenging task, which could limit their implementations for on-line systems. Developing more efficient algorithms for data processing procedures, especially selection of essential spectral bands is obviously necessary.

In terms of practical applications, hyperspectral imaging technique has the potential to detect more quality attributes of chicken meat, which are less exploited, including color, bruise

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and chemical composition distribution. The surface appearance of chicken is a very important index for indicating the freshness and wholesomeness and consumers are always willing to pay a higher price for such product with good surface appearance. Therefore, chickens with surface defects must be separated from the wholesome chickens during the grading operation. Bruise is one of the major defects occurring on chicken skins during handling. Poultry carcasses with bruises affect their quality and lead to the downgrading of the carcasses. Although there is no much literature available in bruise detection, the feasibility of hyperspectral imaging technique is promising for this application. Surface color is also important for evaluating the quality of chicken meat. Hyperspectral imaging technology has great potential in the field of surface color detection due to the similar ability for color determination compared with the colorimeter, and it is believed to have more color information of surface than RGB imaging. Currently, the spoilage determination mainly focuses on TVC. In the future, more specific bacterial for chicken meat should be considered. In addition, the full potential of hyperspectral imaging on grading and classification of frozen-thawed chicken meat should also be exploited in the future work. Furthermore, it is expected that hyperspectral imaging systems will find more substantial and widespread applications in chicken meat safety monitoring and control in different production stages. On the other hand, by combining with other new technologies such as ultrasonic, hyperspectral imaging technique could provide a solution for improving comprehensive quality and safety evaluation of chicken meat.

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Conclusions

This review paper focuses on the principle for hyperspectral image technology as well as relevant studies about chicken meat safety and quality detection and evaluation, including microbiological spoilage detection, contamination detection, tumor detection, quality classification and bone fragments detection. These studies illustrated that hyperspectral imaging technology had great potential in improving chicken meat quality, saving labor costs and increasing economic benefits. However, there are still some aspects of improvement such as finding optimal wavelengths and developing adequately efficient image processing algorithms. Finally, future research should focus on detecting other attributes of chicken meat, which have not been exploited yet, such as color and bruise. It is also expected that hyperspectral imaging technology would be more widely used in the chicken meat safety and quality detection and evaluation with its accurate, efficient and non-destructive advantages.

Acknowledgments

The authors gratefully acknowledge the Guangdong Province Government (China) for its support through the program "Leading Talent of Guangdong Province (Da-Wen Sun)". Specially thanks to Qiong Dai and Nannan Wang from South China University of Technology for their kind suggestions.

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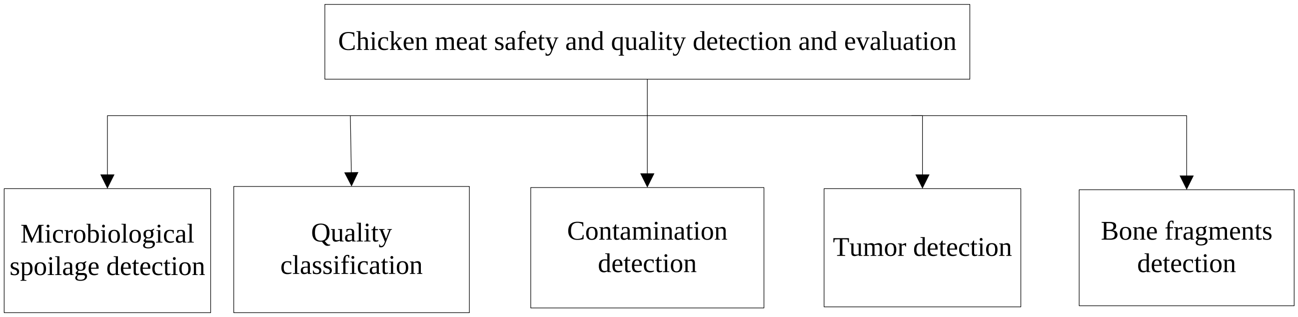

Fig. 1. Chicken meat safety and quality detection and evaluation by hyperspectral imaging technique.

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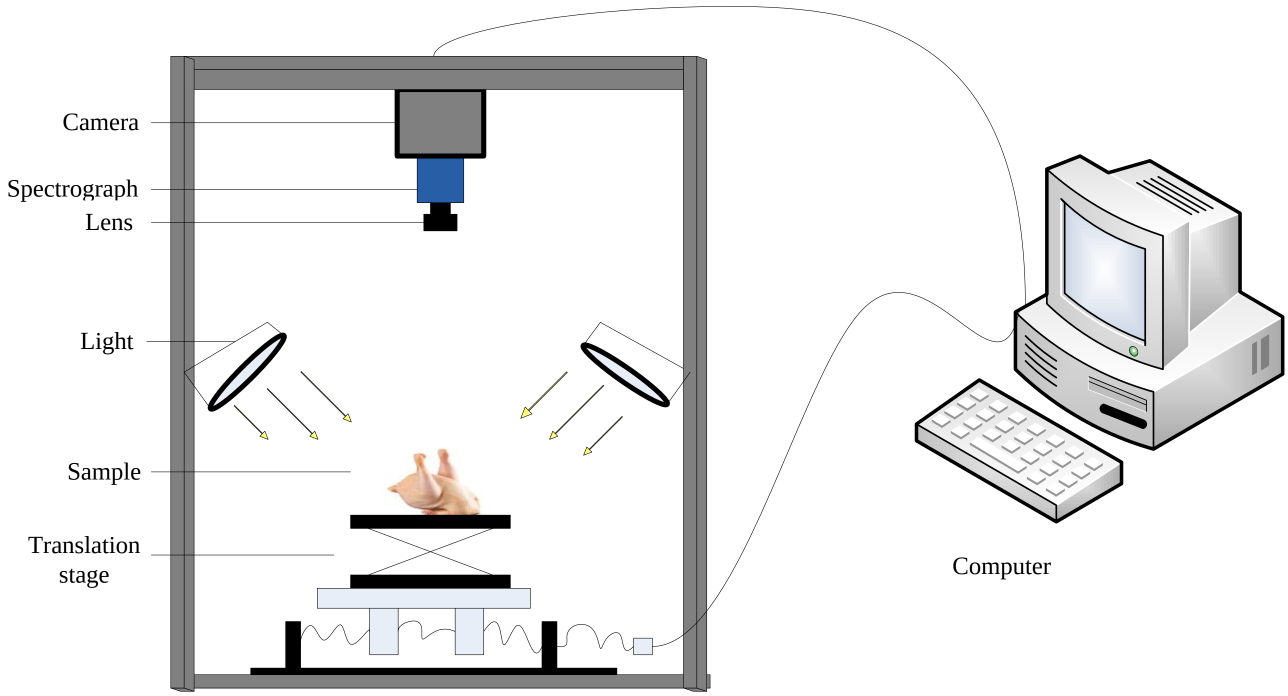

Fig. 2. Components of a pushbroom hyperspectral imaging system.

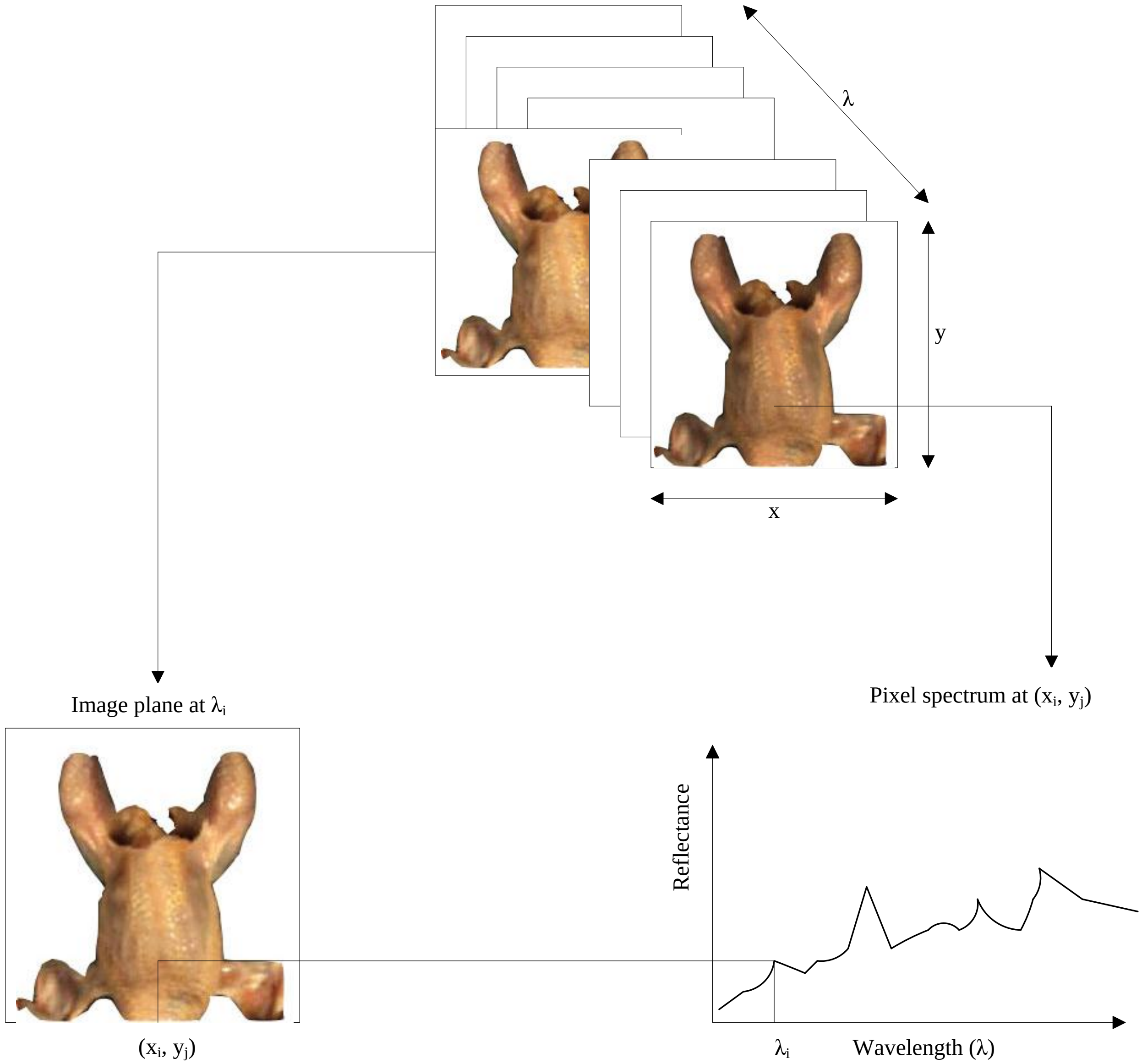

Fig. 3. Schematic representation of hyperspectral imaging hypercube showing the relationship between spectral and spatial dimensions.

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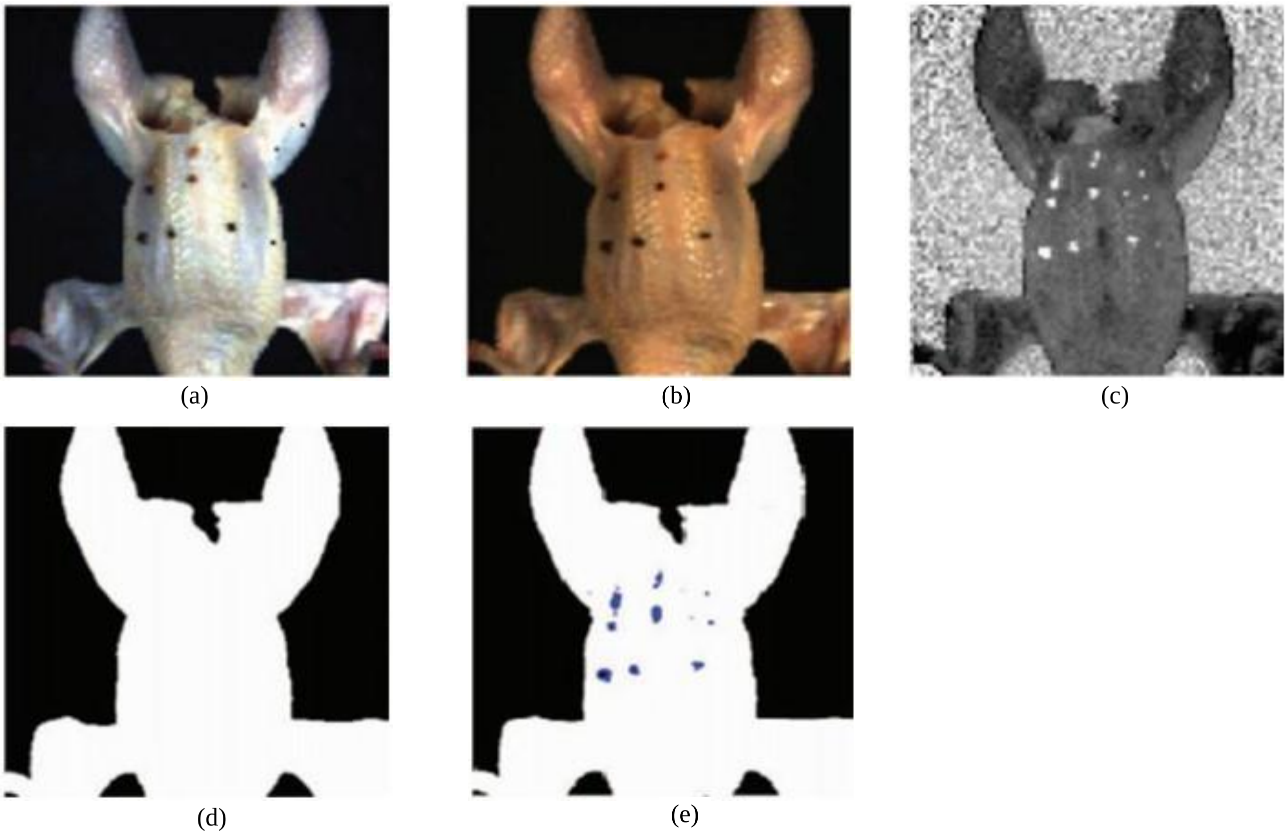

Fig. 4. Visual results of a poultry carcass with the image-processing algorithm applied to a calibrated smoothed pre-processed hyperspectral image. (a) color composite; (b) calibrated color image; (c) ratio image (calibrated and smoothed); (d) background mask; (e) detected contaminants using a threshold of 0.95 with filtering (Park et al., 2006).

Table 1. Applications of hyperspectral imaging technology in safety and quality detection of chicken meats.

Imaging mode	Spectral range (nm)	Application	Data analysis	Accuracy	References
Reflectance	900-1700	TVC determination, Pseudomonas, Enterobacteriaceae	PLSR, GA	0.96, 0.87, 0.88	Feng and Sun (2013a; 2013b); Feng et al. (2013)
Reflectance	430-900	Poultry inspection			Lu and Chen (1999)
Reflectance	385-735	Differentiation of wholesome from unwholesome chicken	Fuzzy algorithm	97.6%, 99%	Chao et al. (2007; 2008)
Reflectance	400-900	Faeces and ingesta detection on the surface of poultry carcasses	PCA	97.3%	Park et al. (2002)
Reflectance	430-900	Detection of fecal contaminants	SAM	90.13%	Park et al. (2007b)
Reflectance	400-900	Contaminants classification	FLDA	98.9%	Park et al. (2007c)
Reflectance	400-1000	Fecal spots identification		91%	Park et al. (2011)
Reflectance	400-1024	Contaminant detection on poultry carcasses	STLR	100%	Windham et al. (2003)
Reflectance	400-1000	Ingesta contamination detection	A decision tree classifier algorithm	100%	Windham et al. (2005)
Reflectance	400-900	Detection of surface contaminants		98%	Lawrence et al. (2006)
Fluorescence	425-711	Skin tumor detection		76%	Kim (2004)

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Fluorescence	425-711	Skin tumor detection	SVM, PCA	96%, 90.6%	Du et al. (2007); Fletcher et al. (2003)
Fluorescence	425-711	Skin tumor detection	Fuzzy inference	82%	Kong et al. (2004)
Reflectance	430-900	Skin tumor detection	PCA	96.4%	Park et al. (2006)
Reflectance	420-850	Skin tumor detection	PCA	86%	Chao et al. (2000)
Reflectance	400-1024	Skin tumor detection	ABB, MBB	91.6%, 80%	Nakariyakul et al. (2006; 2009)
Reflectance	420-720	Skin tumor detection	PCA, DWT, KDA	95.3%	Xu et al. (2007)
Reflectance/transmittance	400-1000	Bone fragment detection in chicken breast fillets	PCA	100%	Yoon et al. (2006; 2008)

PLSR: partial least squares regression, GA: genetic algorithm, PCA: principal component analysis, SAM: spectral angle mapper, FLDA: fisher linear discriminant analysis, STLR: single-term linear regression, DWT: discrete wavelet transform, KDA: kernel discriminant analysis, MBB: modified branch and bound, ABB: adaptive branch and bound, SVM: support vector machine.

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