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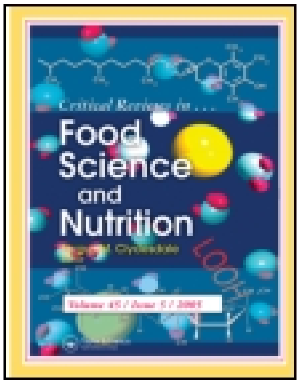

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Meat Quality Evaluation by Hyperspectral Imaging Technique: An Overview

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During the last two decades, a number of methods have been developed to objectively measure meat quality attributes. Hyperspectral imaging technique as one of these methods has been regarded as a smart and promising analytical tool for analyses conducted in research and industries. Recently there has been a renewed interest in using hyperspectral imaging in quality evaluation of different food products. The main inducement for developing the hyperspectral imaging system is to integrate both spectroscopy and imaging techniques in one system to make direct identification of different components and their spatial distribution in the tested product. By combining spatial and spectral details together, hyperspectral imaging has proved to be a promising technology for objective meat quality evaluation. The literature presented in this paper clearly reveals that hyperspectral imaging approaches have a huge potential for gaining rapid information about the chemical structure and related physical properties of all types of meat. In addition to its ability for effectively quantifying and characterizing quality attributes of some important visual features of meat such as color, quality grade, marbling, maturity, and texture, it is able to measure multiple chemical constituents simultaneously without monotonous sample preparation. Although this technology has not yet been sufficiently exploited in meat process and quality assessment, its potential is promising. Developing a quality evaluation system based on hyperspectral imaging technology to assess the meat quality parameters and to ensure its authentication would bring economical benefits to the meat industry by increasing consumer confidence in the quality of the meat products. This paper provides a detailed overview of the recently developed approaches and latest research efforts exerted in hyperspectral imaging technology developed for evaluating the quality of different meat products and the possibility of its widespread deployment.

Keywords Beef, poultry, fish, pork, computer vision, spectroscopy, hyperspectral imaging, image processing, near infrared, NIR, spectroscopy, spectrometry

INTRODUCTION

Discoveries and innovations in meat science during the last century have led to revolutionary changes in meat production, processing, marketing, and consumption (Beermann, 2009). Generally, meat is the most valuable livestock product and for many people serves as their first-choice source of animal protein. Determination of meat quality parameters has always been very essential throughout all processes of the food industry because consumers are always demanding superior quality of meat and meat products (Desmond et al., 2000; McDonald and Sun, 2001; McDonald et al., 2001; Wang and Sun, 2002a,b). Interest in meat quality is driven by the need to supply the consumer with a consistently high quality product at an affordable price. Indeed, high quality is a key factor for the modern meat industry because a high quality product is the basis for success in today's highly competitive market. Meat is a perishable, nutritious, and expensive food commodity, and its quality is related to individual experience and preference. Although the consumer decides which kind of products are more desirable, the ultimate quality of meat is a direct integration of parameters and conditions such as feeding and management of the animals during their growth, pre-slaughter stress, stunning method, electrical

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stimulation, cooling method and rate, maturing time, freezing and thawing, and cooking conditions as well as handling and processing techniques and composition of meat products (Liu et al., 2003). Meat quality can be defined in terms of consumer appreciation of texture, flavor, and food safety, which includes both the health implications of compositional and microbiological properties. Regrettably, the great variability in raw meat leads to highly variable products being marketed without a controlled level of quality. This problem is aggravated when the industry is unable to satisfactorily characterize this level of quality and cannot therefore market products with a certified quality level (Damez and Clerjon, 2008).

Traditional quality evaluation methods such as the Warner-Bratzler apparatus to measure maximum shear force for expressing meat tenderness and impedance measurements for detecting frozen meats and fat content are destructive, time consuming, laborious, costly, and require lengthy sample preparation, which are associated with inconsistency and variability due to human differences (Shackelford et al., 1995; Damez et al., 2008). Therefore, these methods are not practical when fast analysis and early detection of quality parameters in industrial and commercial processing are required (Ariana et al., 2006; Bonifazi and Serranti, 2008). The current trends in monitoring meat quality are to move the measurements of quality from the laboratories to the processing lines. These factors accentuate the need for objective measurement systems due to the fact that the meat industry needs reliable meat quality information throughout the production process in order to guarantee high-quality meat products for consumers (Damez and Clerjon, 2008). The expectations of consumers for meat quality grow constantly, which induces the necessity of quality control at several stages of meat industry such as slaughtering, meat cutting, and distribution (Monin, 1998). Objective and fast assessment of meat quality have been desirable for a long-time in the industry and there have been many research efforts in developing the required instrumentation. Different techniques and methodologies based on different principles, procedures, and/or instruments are currently available for measuring different meat quality attributes.

Over the past few years, a number of methods have been developed to measure meat quality traits in objective ways (Abouelkaram et al., 1997; 2006; Liu et al., 2003; Vote et al., 2003; Shackelford et al., 2005; Zell et al., 2009). Imaging technique is one of these methods that have been applied for visual evaluation of meat and other food quality and for rapidly identifying quality problems on the processing line with the minimum of human intervention (Brosnan and Sun, 2004; Du and Sun, 2004, 2006; Fathi et al., 2010; Kumar and Mittal, 2009; Mizrach et al., 2009; Pallottino et al., 2010; Schlüter et al., 2009; Shankar et al., 2008; Singh et al., 2008; Wu et al., 2008; Yang et al., 2009; Zheng et al., 2006a,b). On the other hand, spectroscopic technique is another increasingly growing technique due to its rapidity, simplicity, and safety, as well as its ability to measure multiple attributes simultaneously without monotonous sample preparation. Throughout the last century, spectroscopy was widely used to detect the chemical composition of meat and meat products. Near infrared spectroscopy (NIRS) was always one of the most promising techniques for large-scale meat quality evaluation. Nowadays, NIRS is successfully used in many fields including food quality assessment. A number of advantages have been offered by NIRS technology over traditional quality evaluation methods such as rapid and frequent measurements, no sample preparation is required, suitability for on-line and at-line use, and simultaneous determination of different attributes. The main disadvantages of the method are its dependence on the reference method, weak sensitivity to minor constituents, limited transfer of calibration between different instruments, complicated spectral data interpretation, and particularly, the low spatial resolution for analysis of food samples with non-homogeneous composition as in meats and meat products (Prevolnik et al., 2004).

The conventional spectroscopic technique alone is not able to provide some fundamental information where spatial distribution of quality parameters is essential to be demonstrated because it analyzes the sample in bulk and determines an average composition across the entire sample. Hyperspectral imaging has thus emerged to integrate both spectroscopic and imaging techniques in one system to cope with the increasing demand of safe foods. Also known as "imaging spectroscopy or imaging spectrometry," hyperspectral imaging technology is based on the utilization of an integrated hardware and software platform that combines conventional imaging and spectroscopy to attain both spatial and spectral information from each pixel. There is currently a wide set of applications utilizing hyperspectral technology ranging from the analysis of food products in laboratory, to real-time application in line inspection for detecting disease and contamination. In recent years there has been a growing interest in this technology from researchers around the world for non-destructive analysis in many research and industrial sectors (ElMasry et al., 2007; 2008; Kim et al., 2004; Cluff et al., 2008; Bonifazi and Serranti, 2008; Naganathan et al., 2008a; 2008b). Although these systems have not yet been sufficiently exploited for meat quality assessment, their potential is promising. This paper thus provides an overview of the traditional meat quality assessment techniques with emphasize on hyperspectral imaging technology to substitute these methods. Also, the paper highlights the basic fundamentals of hyperspectral imaging and the most recent advances in the application of hyperspectral imaging for different kinds of meat (i.e., beef, pork, poultry, and fish).

MEAT QUALITY ASSESSMENT

In recent years, the concept of food quality has received a lot of attention from food producers and retailers as well as from public authorities and health educators. Generally, the quality of food covers many aspects, such as functional, technological, sensory, nutritional, toxicological, regulatory, and ethical aspects. Functional and technological quality is related to the processing and storing of the food and is traditionally measured by physical and chemical methods, while the sensory quality is the eating quality as experienced by the consumer. A need for ethical quality exists in meat production, where handling of live animals is critical. Meat quality is traditionally measured by chemical, physical, and sensory methods (AMSA, 2001). Some of these methods are quite time consuming, laborious, and destructive. Today, it is possible to replace most of these inconvenient methods by instrumental techniques. From the viewpoint of quality assurance, it is desirable to inspect all products and thus an ideal sensing method for the meat industry would be on-line and non-destructive. The suggested system should be able to predict chemical composition (crude protein, intramuscular fat, moisture/dry matter, ash, gross energy, myoglobin, and collagen content), physico-mechanical parameters (pH value, color, water holding capacity, Warner–Bratzler, and slice shear force), and sensory attributes (color, shape, marbling, odor, flavor, juiciness, tenderness, or firmness).

The visual appearance, textural patterns, geometrical features, and color of fresh meat products are all important criteria used by consumers for purchasing high quality meat. These parameters are linked to some chemical properties such as water holding capacity, marbling, and protein contents. The purpose of evaluating meat quality is to identify physical attractiveness and to predict the palatability of the cooked lean meat. Visible quality traits are not precise palatability predictors, but are useful indicators to identify cuts that will be tender/tough, juicy/dry, and flavorful/off-flavor cooked products. The main quality features to be evaluated include color, firmness and texture of the lean, degree of marbling, and color of fat for beef, pork, veal, and lamb. Poultry and fish are not in this classification because of the difference in lean and fat content and color patterns and because they have a negligible fat content.

Quality grade of a carcass is determined according to the kind of meat, animal gender, and maturity based on color, texture, marbling, and firmness of the ribeye muscle. In practice, the quality of meat is normally assessed subjectively by an experienced grader. This method relies greatly on human skills leading to subjectivity among different analysts. Because quality assurance is one of the most important goals of any industry, an objective and non-destructive method for fast classification of meat quality is highly required by the meat industry (AMSA, 2001). As suggested by Monin (1998), the key words of success for any proposed evaluation technique in the meat industry are:

- existence of a real need and an assured (not only hypothetical) benefit;
- direct relation to the desired quality traits of the end product;
- reasonable prediction accuracy;
- realistic cost, taking into account the unitary value of the evaluated carcasses or joints;
- rapidity, to comply with slaughter, cutting, or packing rates of several hundreds or even thousands per hour;
- potential full automation, particularly when high rates of measurements are needed;
- non-invasiveness, as with the continuously increasing concern of safety, non-invasive techniques will be clearly preferred.

Traditional Methods

There is an assortment of traditional methods and techniques used in research, industry and processing lines for quality assessment of meat and meat products. Most of these methods do not fulfil the basic needs of precision, sanitation, and expeditiousness required for the modern food processing facilities. In addition, the limitation of these methods is that they are only capable of sampling either a very small area or a very small number of the overall products, and therefore do not lend themselves to high-speed production processes. Furthermore, these traditional options are costly, owing to the labor and reagents required to do the testing, poor sampling rates, and the time required for analysis. Meat inspection technology for high-volume food processing lines requires instrumentation that is specific to the processed product, robust, and durable enough for the harsh environments of processing plants. They also have to be cost-effective to reflect the competitive nature of the food and agriculture markets. In meat, it is important to assess the main quality traits such as color, marbling, water-holding capacity, drip loss, pH, moisture, and tenderness in such a way as to be non-destructive, safe, fast, and precise with minimum sample preparation.

Color

Color is an important feature that is used in conjunction with other characteristics to determine the grade or suitability of meat for a particular market. Meat color has a huge influence on the consumer appeal of a product. As consumers evaluate product quality partly by appearance, an attractive and stable color in the meat has a major influence on the buying decision taken by the consumer. Meat purchasing decisions are influenced by color more than any other quality factors because consumers use discoloration as an indication of freshness and wholesomeness. The appearance of meat and meat products is a complex topic involving animal genetics, ante- and post-mortem conditions, fundamental muscle chemistry, and many other factors related to meat processing, packaging, distribution, storage, display, and final preparation for consumption (Mancini and Hunt, 2005). There are a number of interacting factors during processing that can have a significant impact on meat color, including electrical stimulation, chilling rate, bloom time, and dark cutting meat. Color is an extremely subjective and personal parameter because it is very difficult to attribute numbers to the brains reaction to visual stimuli. Color in meat is related to the level of the protein pigment, myoglobin, present in the muscle. Myoglobin is the principal protein responsible for meat color, although other heme proteins such as hemoglobin and cytochrome C may also play a role in beef, lamb, pork, and poultry color (Mancini and Hunt, 2005). Also, meat color depends on pigment concentration, pH, the amount of intramuscular fat (IMF), and oxido-reduction status (Monin, 1998). The concentration of myoglobin in grams per kilogram of lean meat is higher in beef than lamb and pork, while poultry exhibits the least amount of myoglobin (Feiner, 2006). The color of meat can be estimated in two main ways: chemically by analyzing the pigments present or physically by measuring the interaction of light with meat sample. Several methods are available for objectively measuring the color of foods, some of which depend on the extraction of pigments from food products followed by spectrophotometric determination of pigment concentration. Other simpler methods consist of numerous combinations of percentage reflectance values and tristimulus values. Color measurements through interaction of light are usually done using the Commission International De I' Eclairage (CIE) color system, that provides the reference standard CIELAB or CIEXYZ color spaces (Commission International De I' Eclairage, 1978; Agulló et al., 1990; Yam and Papadakis, 2004; Feiner, 2006). However, because color images are typically produced for a wide variety of viewing environments, the International Color Consortium (ICC) has defined a Color Management System (CMS) that provides a means for communicating color information among input, output, and display devices. Currently, many options are available for instrumental color analysis (e.g., colorimeters and spectrophotometers). Each instrument offers a variety of options that allow choosing from various color systems (Hunter, CIE, and tristimulus); Illuminants (A, C, D65, and Ultralume); angle of observation and aperture sizes.

There are so many color spaces including hardware-orientated spaces (RGB (Red Green Blue), CMY(K) (Cyan Magenta Yellow (Black), suited for image acquisition and display), human-orientated spaces (HSL (Hue Saturation and Lightness), CIE XYZ, CIE YUV, CIE $L^*u^*v^*$, and CIE $L^*a^*b^*$, which give consideration to human sensory perception and are suited for image description and interpretation), and instrumental spaces, by which the meat color can be specified. Color space allows objective specification and visualization of color. The CIE is defined as a system that classifies color according to the HVS (the human visual system). Using this system any color can be specified in terms of its CIE co-ordinates and hence be confident that a CIE defined color will match another with the same CIE definition. In most common instruments, color is usually measured in the $L^*a^*b^*$ scale, where L^* denotes the brightness, a^* the red-green color and b^* the blue-yellow color axis. Based on color measurements, meat can be broadly classified as "red" or "white" depending on the concentration of myoglobin in muscle fiber. The simplest way currently used in most production units for determining meat color is usually carried out by comparing the color of the rib eye muscle (M. *longissimus dorsi*) on the chilled carcass and scored against the meat color reference standards in that area of the M. *longissimus dorsi* that displays the predominant color. Even though color assessors are well trained, the subjective nature of color assessment means that there can be variability in grading scores between assessors which stimulates the need for more objective ways.

Moisture, Drip Loss, and Water Holding Capacity

Moisture as a general term is the total water content of meat. A smaller portion of water (1%) is tightly bound to protein and salt structures and known as the bound water. The moisture content of meat is an important criterion because meat is sold by weight, so that any depletion of water affects the economic profits of meat product. Besides, the water content of meat determines to a large extent the juiciness of meat and thereby the eating quality. One of the traditional methods for determining meat moisture content is the oven drying method. Moisture is lost after slaughter in the form of drip while the carcass is still in the chilling room and while fresh consumer cuts are in the retail display counter. Although drip loss has been measured for years, an international standard procedure is still absent (Otto et al., 2004). Other traditional methods for determining drip loss are the filter paper method (Kauffman et al., 1986), the bag method (Honikel, 1998), the tray method (Lundström and Malmfors, 1985), and the EZ-DripLoss method (Rasmussen and Andersson, 1996). The disadvantages of these methods are that they are performed late in the slaughter process, after cutting. Sorting at this stage in the slaughter process is of little value to the packing plant. Moreover, due to the variation in these methods, the results for drip loss in the literature are difficult to compare, and therefore there are still efforts being made to find more suitable methods for determination of this important criterion.

Water holding capacity (WHC) is the ability of meat to hold all or part of its own water during application of external forces, cutting, grinding, pressing, or heating (Zayas, 1997). This ability depends on the way by which the meat is handled, which also determines the juiciness of meat. From the processor point of view, it is important to predict the water holding capacity of meat because it is technologically and financially important for the food processing industry due to the fact that WHC is an indication for weight loss in raw, cooked, and processed meats. Unfavorable water holding capacity or drip loss causes major problems in the meat industry due to its negative impact on the appearance of meat and the yield in further processing. It is also responsible for poor color in cured meat products, such as ham, and can influence meat palatability traits (Toldrá and Flores, 2000). Various methods have been utilized for determining WHC such as drip loss, cooking/heating loss, centrifuge force method, thawing loss, processing loss, Napole yield, and technological yield (Prevolnik et al., 2010). Even within the same methodological approach there exist several techniques. For instance, WHC determined by drip loss could be performed by using bag method, meat-juice container procedure (EZ drip loss), tray drip loss, or the filter paper method. Furthermore, the values of WHC depend on many factors such as sampling site, size, and shape of meat samples, type and duration of treatments, and the physical principle of water release, which leads to considerable differences in the results among studies. Although the methods for the assessment of water holding capacity are rather simple, they are time-consuming and destructive and thus unsuitable for on-line requirements. Difficulties in measuring WHC in meat processing plants in industrial applications require establishing novel, rapid, non-invasive techniques to overcome the drawbacks of traditional methods.

Tenderness

Tenderness is an expression of meat texture which is considered as the most important sensory quality attribute associated with consumer satisfaction, as consumers regard tenderness as the primary factor in eating satisfaction, which is also positively related to juiciness and flavor, and thus they accept to pay more for tender meat (Lusk et al., 2001; Winger and Hagyard, 1994). Meat tenderness is much related to the structure of the muscle and the biochemical activity aging period between slaughtering and consumption. Indeed, meat texture is a complex phenomenon that encompasses characteristics such as hardness, springiness, chewiness, cohesiveness, and even juiciness (AMSA, 2001). Sources of tenderness variation in beef may be attributed to the animal's age, sex, breed, and antemortem stress, as well as post-mortem treatments (Muchenje et al., 2009). For instance, refrigerating carcasses directly after slaughtering results in a severe contraction of the muscle fibers, causing an undesirable hardness in meat in a phenomenon best known as "cold shortening" (Razminowicz et al., 2006).

The most common way to assess meat tenderness is measuring the mechanical properties of meat sample using a Warner-Bratzler shear force (WBSF) or slice shear force (SSF). For WBSF determination, six cylindrical, 1.27-cm-diameter cores are typically removed from each steak; while for SSF determination, a single 1-cm-thick, 5-cm-long slice is removed from the lateral end of each sample. For both techniques, samples should be removed parallel to the muscle fiber orientation and sheared across the fibers. WBSF uses a V-shaped blade, while SSF uses a flat blade with the same thickness and degree of bevel on the shearing edge. However, these two methods are not suitable for the commercial and fast-paced production environment. In the meat marketing system, beef products leave the packing plant at about three days post-mortem, and reach the consumer after approximately 14 days. The beef industry needs an instrument that can scan fresh meat at 2–3 days post-mortem and predict ultimate 14-day cooked-beef tenderness (Price et al., 2008). There is a growing concern to incorporate beef tenderness measurement into quality grading processes. As a result, the development of an instrument for fast and non-destructive prediction of meat quality is a top priority for the meat industry. Hyperspectral imaging techniques have the promising potential of assessing all the major quality parameters of meats.

Intramuscular Fat (IMF)

Intramuscular fat (or marbling) is the name of the white flecks of fat present within the lean in the muscle, and the marbling score is a measure of the distribution density of fat in the carcass rib-eye region. Marbling deposition is classified according to the amount of intramuscular fat distributed in the muscle and varies among species and tends to increase with age. It contributes positively to eating satisfaction, as retail cuts with little marbling are likely to result in cooked products that lack flavor and juiciness. As marbling enhances juiciness, it should be uniformly and finely distributed throughout the lean, as this is preferred by consumers over marbling that appears as large, coarse flecks of intramuscular fat (Fernandez et al., 1999). Unfortunately, in most abattoirs assessing marbling is usually conducted visually in a subjective way by comparing the proportion of intramuscular fat within the M. *longissimus dorsi* against marbling reference standards specific for each of the meat species. At present, the score of beef marbling is largely determined by the subjective experience of the graders who must be highly qualified personnel. While humans can be trained to reliably assess marbling, the fact remains that it is a subjective judgment and consequently, consistency between marbling assessors can often vary. An objective method that could evaluate marbling and/or fat content and characteristics would help meat producers to select better breeds capable of producing meat with good IMF distribution and consequently with improved eating quality. Regarding technologies currently under development, image analysis would appear to offer considerable promise given that the technology essentially emulates what trained assessors do. Recent advances in computer technologies and color image processing techniques have increased the effectiveness of image analysis in measuring marbling fat properties. Thus, the marbling level could be determined with varying degrees of success using image analysis technique (Gerrard et al., 1996; Faucitano et al., 2005; Chen and Qin, 2008).

Novel Techniques

Computer Vision

Computer vision techniques based on the analysis of digital images are currently used widely for visual evaluation of meat joints and cuts. This technique is based on the analysis of spatial information acquired from the digital image of an object, which includes geometrical, size, appearance, and color features. Computer vision utilizing imaging technique has been developed as an inspection tool for quality and safety assessment of a variety of meat products. The flexibility and the non-destructive nature of this technique help to maintain its attractiveness for applications in the food industry (Cubero et al., 2011; ElMasry et al., 2008). Computer vision has been seen as a potential solution for various automated visual quality evaluation processes.

Image processing and image analysis are the core of computer vision, involving mathematics, computer science, and software programming. As the automated visual inspection is the most common and rapid way for the quality assessment of meat products applied to production chain, machine vision has been recognized as a promising approach for the objective assessment of meat quality. Image processing has the proven ability to assess basic acceptability traits, namely color and marbling; it is totally non-invasive and obviously use of this technology could greatly improve quality control in the meat industry. Computer vision systems have found widespread usages in quality evaluation of different meat products and in the analysis of surface defects and color classification (Quevedo et al., 2008). Color and textural features are some representative image features that could be used to predict and estimate some key quality parameters of meat (Li et al., 1999; 2001; Quevedo and Aguilera, 2008). However, it is important to differentiate between the texture used to express roughness or smoothness of the surface of the meat sample in an image and the real texture of a meat sample used to express the mechanical properties or tenderness of this sample. In image analysis, textural features represent the spatial distribution of tonal variations and the spatial arrangement of the grey levels of the pixels in a region of an image (Kavdır and Guyer, 2004).

Unfortunately, computer vision is ineffective for classifying objects having similar colors, for detecting invisible defects; and for predicting quality attributes (e.g., chemical composition). Although external attributes such as size, shape, color, texture, and external defects can be easily evaluated by ordinary computer vision, internal attributes are difficult to be detected with relatively simple and traditional imaging means (Du and Sun, 2004). Imaging technology is most effective when quality attributes of a product are related to its extrinsic characteristics, but it becomes less effective or ineffective when quality attributes are mainly determined by the intrinsic properties of the product, such as composition and internal physical characteristics, which are not readily detectable at the surface (Lu and Chen, 1998).

Spectroscopy

Basically, spectroscopic methods provide detailed fingerprints of the biological sample to be analyzed using physical characteristics of the interaction between electromagnetic radiation and the sample material, such as reflectance, transmittance, absorbance, phosphorescence, fluorescence, and radioactive decay. Recently, near-infrared spectroscopy (NIRS) techniques have received considerable attention and been accepted among researchers as a means for non-destructive sensing of meat quality as NIRS has the potential for simultaneously measuring multiple quality attributes in a fast and non-destructive way and without lengthy sample preparation. In this technique, it is possible to obtain information about the compositional parameters of the tested samples based on the spectral features of the sample, but it is not easy to know the location of such information due to its limited spatial resolution. Applications of near-infrared spectroscopy have been increased in food product quality analysis, and it has been widely used to predict the quality parameters of fresh meat such as tenderness (Venel et al., 2001; Andrés et al., 2008; Prieto et al., 2008; Rust et al., 2008); color, cooking loss and sensory characteristics (Prieto et al., 2009) and pH, water holding capacity, and drip loss (Chan et al., 2002; Andrés et al., 2008) in order to substitute other commonly used destructive methods. Unfortunately, NIRS is unable to provide constituent gradients due to the fact that NIRS techniques rely on only measuring the aggregate amount of light reflected or transmitted from a specific area of a sample (point measurement where the sensor is located), and does not contain information on the spatial distribution in the sample. Furthermore, spectroscopic assessments with relatively small point-source measurements do not contain spatial information, which is highly important in many food inspection applications. The combination of the strong points from NIR spectroscopic technique and vision technique is the hyperspectral imaging.

Hyperspectral Imaging

Traditional imaging technology provides a high spatial resolution but with limited spectral information, hence, it may not be useful for detecting minor features or chemical concentrations in a sample. Meanwhile spectroscopy alone provides high spectral resolution over both visible and near-infrared spectral regions but with virtually no spatial information (Bonifazi and Serranti, 2008; Ariana and Lu, 2008). Hyperspectral imaging refers to the imaging of a scene over a large number of discrete, contiguous spectral bands such that a complete reflectance spectrum can be obtained for the region being imaged. Hyperspectral images obviously provide much more detailed information about the scene than a normal color camera, which only acquires three different spectral channels corresponding to the visual primary colors (i.e., red, green, and blue). Hence, hyperspectral imaging leads to a vastly improved ability to classify the objects in the scene based on their spectral properties. The spectra on the surface of food materials contain characteristic or diagnostic absorption features to identify a number of pertinent inherent characteristics. Moreover, hyperspectral imaging can provide spectral measurements at the entire surface area of the product while conventional spectrometers only give point measurements. By combining the chemical selectivity of spectroscopy with the power of image visualization, hyperspectral imaging is particularly useful in situations where multiple quality attributes must be considered and when either computer vision or spectroscopy is not suitable. This is due to the fact that hyperspectral imaging enables a more complete description of ingredient concentration and distribution in any kind of heterogeneous samples (Gowen et al., 2008). To judge the overall quality of meat products for classification and grading tasks, multiple extrinsic and intrinsic factors are often needed. For instance, hyperspectral imaging could be an effective technique to grade meat based on both extrinsic, like appearance (e.g., size, intramuscular fat, color), and intrinsic (maturity or tenderness) properties, which are all important in determining the overall quality of meat. The non-destructive nature of hyperspectral imaging is an attractive characteristic for applications on raw materials and final product quality (Wold et al., 2006; Folkestad et al., 2008).

Other Methods

Other novel methods have been tested for meat quality assessment. Foreign objects in deboned poultry can be detected by

X-ray imaging based on X-ray absorption. This technique was combined with the vision system for bone detection in poultry products to overcome X-ray deficiency in detecting small bones, with significant results, although further research was recommended (Vachtsevanos et al., 2000). Ultrasound is another technique applied for composition measurement of chicken meat. Correlation coefficients for fat and moisture content predicted with this technique achieved good results compared to standard methods (Chanamai and McClements, 1999). Moreover, computed tomographic (CT) scanning has been tested for predicting the lean and fat content of pig carcasses with promising results (Haseth et al., 2007; Romvari et al., 2006; Furnols et al., 2009). Because the scope of this review is about hyperspectral imaging system and its potential in meat quality evaluation, some details will be given in the next sections about this system.

HYPERSPECTRAL IMAGING SYSTEM

Basic Principles

Due to the combined features of imaging and spectroscopy, hyperspectral imaging not only provides pertinent extrinsic characteristics of the product (i.e., shape, size, appearance, and color) through image feature extraction, but it can also help in identifying the properties or chemical constituents of the product through spectral analysis. A spectral image is a stack of images of the same object, each at a different spectral narrow band. However, the field of spectral imaging is divided into three techniques called multispectral, hyperspectral, and ultraspectral in addition to panchromatic division in which a spectral image is acquired at only one band. The distinction between all of these spectral images could be attributed to the number of bands at which the images are acquired. Ultraspectral imaging is typically used for spectral imaging systems with a very fine spectral resolution. Hyperspectral imaging systems are distinguished from multispectral imaging systems in two main characteristics: the number of registered spectral bands and spectral resolution. Multispectral imaging systems typically image the scene in just a few spectral bands and have a spectral resolution on the order of 10, while hyperspectral imaging systems acquire images in hundreds of co-registered bands and have a spectral resolution on the order of 100. Also, multispectral imaging systems often have their spectral bands widely and irregularly spaced, while hyperspectral imaging systems have spectral bands that are contiguous and regularly spaced, leading to a continuous spectrum measured for each pixel (Ariana and Lu, 2008). Therefore, multispectral imaging systems do not produce the “spectrum” of an object. On the other hand, hyperspectral deals with imaging narrow spectral bands over a contiguous spectral range, and produce the “spectra” of all pixels in the scene. Compared to the multispectral image, hyperspectral images can increase the detectability of pixels by exploiting finer detail in the spectral signatures of the objects being imaged. As a result of their fine spectral resolution, hyperspectral images provide a significant amount of information about the physical and chemical composition of the materials presented in the image.

Components of Hyperspectral Imaging System

There are three common ways to build one hyperspectral image: tunable filter, whiskbroom, and pushbroom, by which a hyperspectral image can by collected one image at a time, one spectrum at a time, or one line image at a time, respectively. By these ways one- or two-dimensional subset of the hyperspectral image is acquired, thus requiring the temporal scanning of the remaining dimension(s) to obtain a full image. The first way (tunable filter) is conceptually called wavelength scanning because it depends on keeping the sample fixed, and obtaining images one wavelength after another. The other two ways (whiskbroom and pushbroom) are conceptually called spectral scanning since they depend on scanning the specimen in the spatial domain by moving the specimen either point-by-point (whiskbroom) or line-by-line (pushbroom), respectively. Pushbroom acquisition mode is the most common method currently implemented in recent research work in meat quality evaluation. It involves moving the object underneath a stationary imaging system for the acquisition of simultaneous spectral measurements from a sequence of adjacent spatial positions (line-by-line), to complete a volume of spatial and spectral data (Kim et al., 2001; Lawrence et al., 2003). As the camera captures only a line of the illuminated object, the sample is moved past the objective lens on a motorized transactional stage. By scanning the entire surface of the specimen, a complete three-dimensional hyperspectral image called hypercube or data cube is created, where the first two dimensions represent the spatial information and the third represents the spectral information (Lu, 2003). Two-dimensional images acquired at adjacent points on the object are stacked to form a three-dimensional hypercube which may be stored on a hard disk for further analysis.

Pushbroom hyperspectral imaging systems as shown in Fig. 1 are normally composed of the following components: a camera containing a cooled two-dimensional light detector,

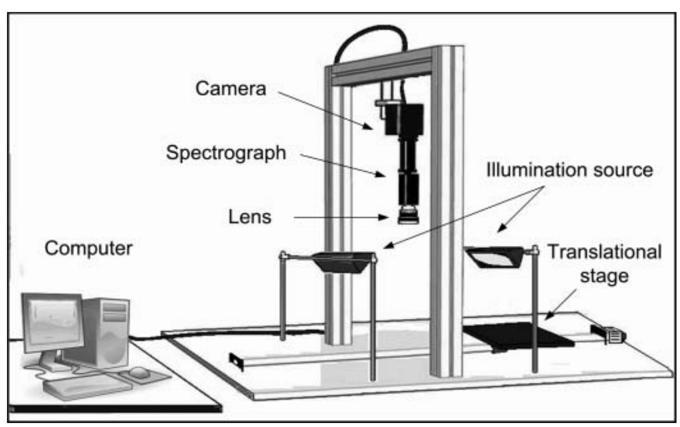

Figure 1 Components of a pushbroom hyperspectral imaging system.

spectrograph, translation stage, illumination units, and a computer supported by image acquisition software. In practice, a camera lens is used to image a scene containing the tested sample onto a narrow slit that is the entrance to the spectrograph. The slit acts as a field stop, allowing only light from along a line on the sample to enter the spectrograph. The light passing through the slit is dispersed by the spectrograph onto a 2-dimensional charged coupled device (CCD) detector array. The length and the width of the "scene line" imaged at a time are thus determined by the slit length and width, by the lens focal length, and by the distance between the sample under investigation and lens. The image of the sample projected through the slit is aligned along one dimension of the CCD (the spatial direction) and the spectrum of each spatial pixel is dispersed along the other dimension of the CCD (the spectral direction). The second spatial dimension of the acquired scene is then constructed as the sample moves forward by the translation stage, causing the image projected on the slit to change continuously as the camera acquires new frames of data. This results in a three-dimensional image "hypercube" with two spatial dimensions and one spectral dimension. Each "slice" of this cube represents an image taken with a specific wavelength, and each pixel in this cube is associated with a spectrum which could be affected by acquisition noise or calibration post-processing. The spatial resolution along the image is determined by the camera pixel size and point spread size of the optics.

To characterize the performance of the whole system, it is pertinent to measure and optimize all parameters that influence the quality of the obtained spectral image. For instance, the ideal illumination should be homogeneous illumination over a large area without radiation damage to the samples. The design of the illumination system is very critical in all applications and must be optimized for each particular application (Driver, 2009). Spectrograph is responsible for limiting and controlling the amount of light reaching the camera, determining the range of wavelength for the image. The two-dimensional light detectors usually used in the camera of the hyperspectral imaging systems are generally photovoltaic semiconductor detectors, so-called charge-coupled device (CCD), or complementary metal oxide semiconductor (CMOS). In some instruments, several different and overlapping detector elements are used for optimized sensitivity in different wavelength regions (Goetz, 2000). The camera, spectrograph, and illumination conditions determine the spectral range of the system.

Hyperspectral imaging system currently employed different spectral ranges to typically yield information from approximately 200 nm (ultraviolet range) to around 2500 nm (NIR range). Hyperspectral imaging system in the visible and very near infrared having a spectral range of 380–800 nm or 400–1000 nm is the most widely used in food analysis applications. Nowadays, hyperspectral imaging systems in the range 900–1700 nm that provide the accuracy required in today's most challenging applications in food analysis are available. Moreover, some hyperspectral imaging systems that cover the shortwave infrared (SWIR) region 900–2500 nm are currently produced by many manufacturers to serve as significant tools in numerous applications in food and agricultural analyses and process analytical technologies. The various spectral resolutions offered by hyperspectral systems enable the detection of subtle differences in spectral signatures thereby improving identification, classification, and prediction capabilities. Choosing suitable spectral resolution is very important for determining the composition and functional properties as well as for detecting defects, diseases, and contaminants in food products (Ariana and Lu, 2008).

A hyperspectral imaging system has to be at least calibrated for distance (spatial), wavelength (spectral), and radiation values (Lawrence et al., 2003; Ariana and Lu, 2008). Calibration of acquired images is commonly performed for both extreme illumination situations: "dark image" and "white reference image." The detectors of the camera usually generate signals due to thermal effects, even when there is no light, which is called "dark current." The dark current is added to the signal produced; therefore, the acquired image should be corrected by deducting this extra signal for further analysis. Such a procedure enables to compensate the offset due to CCD dark current and separates the sample reflectance from the system response (Naganathan et al., 2008a).

Spectral Image

Image Acquisition Modes

Most of the advantages of hyperspectral imaging come from the possibility of using intact (even irregular) samples directly without any particular preparation and providing qualitative and quantitative assessments simultaneously. This fact implies promoting interaction of the radiation with samples to extract the spectral information and generate many different measurement modes. Optical measurements through spectroscopy or imaging techniques are commonly implemented in one of the major four sensing modes: reflectance, transmittance, transflectance, or interactance. In the reflectance mode, the light reflected by the illuminated sample is captured by the detector in a specific conformation to avoid specular reflection. The transmittance mode regards acquiring the image with the light source positioned opposite to the detector and the sample in between; this method is commonly used to detect internal defects of the tested samples. Transflectance is a special way to obtain a transmittance measurement when optical bundle probes are employed. The difference in relation to a simple transmittance measurement is in doubling the optical path as the radiation beam passes twice through the sample. In interactance mode the light source and the detector are positioned parallel to each other; this arrangement must be specially set up in order to prevent specular reflection entering the detector (Nicolai et al., 2007; Ariana and Lu, 2008). Hyperspectral imaging for food products have been usually carried out in the visible-NIR (400–1000 nm) or NIR (1000–1700 nm) range (Lawrence et al., 2003; Qiao et al., 2007; 2007a; 2007b; Naganathan et al., 2008a; 2008b; Park et al., 2006a;

2006b; ElMasry and Wold, 2008). Reflectance is the most common mode in hyperspectral imaging (Park et al., 1998; Ariana et al., 2006; Naganathan et al., 2008a; 2008b), although transmittance and fluorescent modes have also been investigated (Kong et al., 2004; Qin and Lu, 2004; Kim et al., 2004; Ariana and Lu, 2008; Yoon et al., 2008).

Spectral Image Characteristics

Acquired hyperspectral image is known as "hypercube," "spectral cube," "data cube," or "spectral volume." The image is a three-dimensional block of data, comprising of two spatial dimensions (of m rows and n columns) and one spectral dimension (of λ wavelengths) as illustrated in Fig. 2. These images are made up of hundreds of contiguous wavebands for each spatial position of a target analyzed and are typically immense, depending on spatial and spectral resolutions and binning factors. This has implications for storage, management, and further image processing and analyses. The amount of data is the greatest problem that has to be coped with. Assuming to collect an image of 160 wavebands between 900 and 1700 nm (with 5 nm bandwidth) with a spatial dimension of 512×512 pixels and 8 bits precision (1 byte), the size of the image would be $512 \times 512 \times 160$ bytes $= 41.94$ Mega bytes. Therefore, the primary goal of hyperspectral data analysis is to decrease the data size to assist in the identification of few key wavelengths for real-time multispectral imaging implementation.

As a result of spatial and spectral sampling, the fundamental hyperspectral data structure is a data cube whose face is a function of the spatial coordinates and its depth is a function of spectral band (or wavelength). For every band, an image of the sample could be viewed; whereas for each image pixel a spectrum characterizing the materials within the pixel could be drawn; therefore, the hyperspectral image shown in Fig. 2 identified as I(x,y,λ) can be viewed either as a separate spatial image I(x,y) at each wavelength (λ), or as a spectrum I(λ) at every pixel (x,y). Each pixel in a hyperspectral image contains the spectrum of that specific position. The resulting spectrum acts like a fingerprint which can be used to characterize the composition of that particular pixel (Bonifazi and Serranti, 2008), which allows for the recognition of biochemical constituents since regions of a sample with similar spectral properties have similar chemical composition (Goetz, 2000; Lu and Chen, 1998). For instance, the spectral profiles of two different pixels representing different components of a meat steak (lean and fat) are shown in Fig. 2 indicating that these two pixels show different spectral signatures. Therefore, without any further manipulation or pre-processing treatments of these spectral data, the difference in spectral signatures between lean meat pixel and fat pixel of the tested piece of meat shown in Fig. 2 are noticeably distinguished.

Analyzing Spectral Images

Spectral image is considered as an image cube where the third dimension is represented by hundreds of contiguous spectral bands. As a result, a spectral pixel is actually a column vector with dimensions equal to the number of spectral bands in which each component contains specific spectral information provided by a particular channel. Analyzing hyperspectral images and treating their huge data have been a concern for all applications of this technique in identification, detection, classification, quantification, discrimination, visualization, and mapping purposes. Classification enables the recognition of

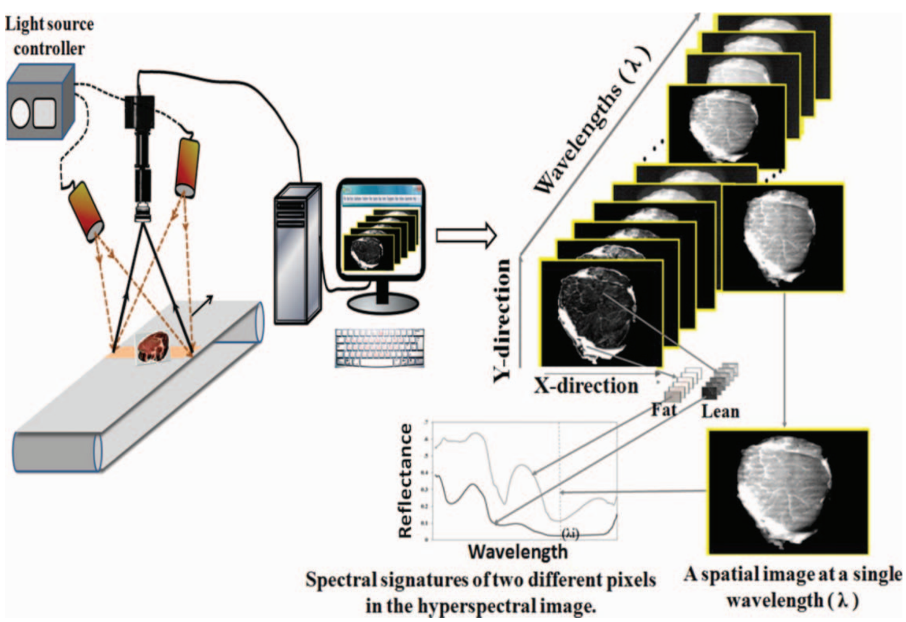

Figure 2 Typical architecture of the hyperspectral imaging system and the resulting "hypercube" for a piece of meat showing the relationship between spectral and spatial dimensions. In addition to spatial information retained in the image, each pixel has its own spectrum. (color figure available online.)

regions with similar spectral characteristics without conducting chemical background determination of these regions.

For quantitative assessment, it is necessary to pull out the hidden chemical information from the hyperspectral images by carrying out correlation between spectral data of tested objects and real quantities or concentrations of such objects using the ordinary laboratory assessments. This step is called the calibration process which needs to be tested and validated with different meat samples. In this aspect, hyperspectral imaging is considered as an indirect method by using obvious correlations between spectral measurements and meat component properties. Taking these calculations and modelling in consideration the main relevant properties involved can help to improve our understanding of meat properties and eating quality. Many conventional statistical and chemometric approaches for complex multivariate analytical methods such as multi-linear regression (MLR), discriminant analysis (DA), principal component analysis (PCA), partial least squares (PLS), and artificial neural networks (ANN) are usually employed for analyzing and classifying hyperspectral images (Park et al., 1998; Naganathan et al., 2008b; Qiao et al., 2007; 2007a; 2007b; Xing et al., 2006; Menesatti et al., 2009). In the spectral domain, a hyperspectral image is characterized by its high dimensionality which needs to be reduced to the most meaningful dimension without losing the informative power of the original image. A dimensionality reduction technique is performed to remove redundant information from the hyperspectral image, thus creating a simplified data. Therefore, various data analysis methodologies comprising of computer programs and algorithms are required for that task to analyze hyperspectral images and then to generate data that describe material properties of the tested samples.

RECENT APPLICATIONS OF HYPERSPECTRAL IMAGING IN MEAT QUALITY EVALUATION

From its manifestation during the mid-1980s as a means of remote sensing explorations, to its current success in several enormous applications, hyperspectral imaging has found extraordinary interests as a key analytical tool for non-destructive evaluation of food products and in the inspection of food for safety and quality. If implemented in processing lines, hyperspectral imaging systems will help to further increase throughput, with precise inspection control over key steps in the production and packaging process. Extracting a chemical signature or "spectral fingerprint" information and its spatial distribution on the product will help producers to correctly sort products according to quality, to screen or eliminate lower quality products before processing or packaging, and to price higher quality products appropriately. Despite the obvious strengths of hyperspectral imaging techniques, the number of scientific papers and technical notes describing their practical use in meat quality evaluation is still limited.

The hyperspectral imaging system has found its way for many important applications such as classification or sorting of food into different groups, either to separate out different types of food items or to sort a single food source into a quality stack. Also, it is used for uniformity monitoring and inspection purposes to exclude contaminated or sub-standard food stuffs from the food-chain with the minimum additional cost. In recent years several investigations have aroused considerable interest in the possible applications of hyperspectral imaging for meat products. As a non-destructive and fast inspection method, hyperspectral imaging methods have been intensively studied for determining properties of meat products, but less for meat as compared to horticultural products. Table 1 presents the main research papers published during the last decade where hyperspectral imaging systems were applied for quality and compositional assessment of meat and meat products.

Beef

Attempts on using hyperspectral imaging as a non-destructive method for assessing beef quality have been investigated by several authors. The majority of the studies in beef are focused on tenderness prediction (Cluff et al., 2008; Naganathan et al., 2008a; 2008b; Peng and Wu, 2008) because tenderness is considered the most important factor in the consumer perception of beef palatability (Savell et al., 1989). Tenderness is a property of a cooked product and predicting this property from a fresh steak poses considerable challenges. Direct evaluation of tenderness is not available because there is currently no accepted method available for predicting tenderness on real-time applications. One of the most common ways for predicting tenderness non-destructively is the video imaging technique as an objective technique instead of the destructive methods such as Warner-Bratzler shearing force (WBSF) or slice shearing force (SSF) methods. Research on computer vision-based beef quality evaluation has shown that texture features computed from muscle images are useful indicators of beef tenderness (Du et al., 2008; Jackman et al., 2009). The addition of image texture features to color and marbling parameters significantly improves the accuracy of tenderness prediction (Jackman et al., 2010). On the other hand, several studies have shown that near-infrared reflectance spectroscopy can be used to predict beef tenderness with some successes (Park et al., 1998; Leroy et al., 2003; Andrés et al., 2008). Similarly, to building prediction models of tenderness, the data extracted from spectroscopy should be calibrated against a destructive measurement of tenderness using WBSF or SSF methods.

Recent studies regarding the assessment of beef tenderness using hyperspectral imaging have showed encouraging results. For instance, Naganathan et al. (2008a) and Grimes et al. (2007; 2008) developed a pushbroom hyperspectral imaging system in the visible and near infrared range of 400-1000 nm with a diffuse-flood lighting system to predict tenderness of 14-day post-mortem, cooked beef from hyperspectral images of fresh

Table 1 Applications of hyperspectral imaging technology in quality evaluation of different meat species sorted by product type

Product	Imaging mode	Wavelength range (nm)	Application	Author(s) / year
Beef	Reflectance	496–1036	Tenderness prediction	Cluff et al., 2008
	Reflectance	400–1000	Tenderness prediction	Naganathan et al., 2008a
	Reflectance	900–1700	Tenderness prediction	Naganathan et al., 2008b
	Reflectance	400–1100	Tenderness prediction	Peng and Wu, 2008
	Reflectance	400–1100	Predicting microbial spoilage	Peng et al., 2009
Pork	Reflectance	430–1000	Classification and marbling estimation.	Qiao et al., 2007
	Reflectance	430–980	Classification and determination of color, texture and exudation	Qiao et al., 2007a
	Reflectance	400–1000	Determination of drip loss, pH and color.	Qiao et al., 2007b
	Reflectance	400–1100	Detecting total viable count of bacteria.	Peng and Wang (2008)
Chicken	Reflectance	430–900	Poultry inspection	Lu and Chen, 1998
	Reflectance	400–1000	Detection of fecal contaminants	Heitschmidt et al., 2007
	Fluorescence	425–711	Skin tumor detection	Kong, 2003; Kong et al., 2004
	Reflectance	400–900	Detection of surface contaminants	Lawrence et al., 2004
	Reflectance	447–733	Skin tumors detection	Nakariyakul and Casasent, 2004; 2007b
	Reflectance	400–1024	Contaminant detection on poultry carcasses	Nakariyakul and Casasent, 2007a
	Reflectance	400–900	Faeces and ingesta detection on the surface of poultry carcasses	Park et al., 2002
	Reflectance	430–900	Detection of fecal contaminants	Park et al., 2006b
	Reflectance	400–900	Contaminants classification	Park et al., 2007
	Reflectance/ Transmittance	400–1000	Bone fragment detection in chicken breast fillets	Yoon et al., 2006; 2008
	Reflectance	400–1000	Online inspection and differentiation of wholesome from diseased chicken	Yang et al., 2009
Fish	Transflection	400–1000	Ridge detection and automatic fish fillet inspection	Sivertsen et al., 2009
	Interactance	760–1040	High-speed assessment of water and fat contents in fish fillets	ElMasry and Wold, 2008b
	Reflectance	892–2495	Determination of fish freshness	Chau et al., 2009
	Transmittance	400–1000	Detection of nematodes and parasites in fish fillets	Wold et al., 2001; Heia et al., 2007
	Interactance	760–1040	Distribution of fat and salt contents in fish fillets.	Segtnan et al. (2009; 2009)

beef-ribeye steaks (M. *longissimus dorsi*) between the 12th and 13th ribs (n = 111). Slice shear force values were measured as a tenderness reference and samples were classified in three different categories, namely tender (SSF $\leq$ 205.80 N), intermediate (205.80 N $<$ SSF $<$ 254.80 N), and tough (SSF $\geq$ 254.80 N). After reflectance calibration, a region-of-interest (ROI) of 200 $\times$ 600 pixels at the center of each steak was selected and principal component analysis (PCA) was carried out on the ROI images. The first five principal components explained over 90% of the variance of all spectral bands in the image. Then, Gray-level textural co-occurrence matrix (GLCM) analysis was conducted to extract second-order statistical textural features from the principal component images. With a leave-one-out cross-validation procedure, the model predicted the three tenderness categories with an accuracy of 96.4%. The result indicated that hyperspectral imaging was able to identify all tough samples and has considerable promise for predicting beef tenderness. However, before suggesting this method for industrial implementation, the model must be validated with a new and a larger set of samples. This hyperspectral imaging system developed is an off-line system which needs 10 s to acquire an image of a beef steak, and 10 min to assign a tenderness category. This time could be reduced significantly by reducing the high dimensionality of the hyperspectral images to form a multispectral imaging system consisting of a few important spectral wavebands for definite applications.

In another attempt to enhance the performance of hyperspectral imaging system for classifying beef steaks based on their tenderness, Naganathan et al. (2008b) repeated the same protocol explained in Naganathan et al. (2008a) but used a hyperspectral imaging system in the spectral range of 900–1700 nm to predict 14-day aged, cooked beef tenderness from the hyperspectral images of fresh ribeye steaks (n = 319) acquired. They used partial least squares regression (PLSR) instead of PCA and the SSF value as a reference tenderness, and then PLSR loading vectors were obtained. This model correctly classified 242 out of 314 samples with an overall accuracy of 77.0%. Also, some optimal wavelengths (1074, 1091, 1142, 1176, 1219, 1365, 1395, 1408, and 1462 nm) corresponding to fat, protein, and water absorptions were identified.

Light scattering could potentially be used as an indicator of beef tenderness and the changes in scattering profiles are believed to represent the changes in tenderness. The hyperspectral imaging system can be used to collect the scattering profile of light coming from the beef sample with very high spatial and spectral resolutions with short acquisition times. The scattered light can thus be captured with high spatial resolution at many wavelengths simultaneously in the hyperspectral image. Cluff et al. (2008) developed a non-destructive method using the hyperspectral imaging system (496-1036 nm) for predicting the tenderness of cooked beef (44 strip loin and 17 tenderloin cuts) by optical scattering of light on fresh beef muscle tissue. In total, 40 hyperspectral images representing scattering profiles at 40 different locations in each steak were acquired, and then these images were averaged to produce a representative hyperspectral image with a high signal-to-noise ratio. The results indicated that tenderness expressed as WBSF values could be predicted with an $R = 0.67$, indicating that the optical scattering implemented with hyperspectral imaging has not proved a remarkable success for predicting current status of tenderness in beef steak. If the predicted WBSF values were used to classify the samples into categories "tender" and "intermediate" (there were no "tough" samples) as described by Naganathan et al. (2008a), the accuracy would be 98.4%.

Peng and Wu (2008) used a laboratory hyperspectral imaging system in the visible/NIR range between 400 and 1100 nm for assessing tenderness in 5-day aged beef. By applying a multi-linear regression (MLR) approach they identified the wavelength of 772 nm as the most correlated wavelength with beef tenderness expressed as WBSF. Results showed that the extracted spectral characteristics of hyperspectral images could successfully predict tenderness with a high correlation coefficient (r) of 0.94 and standard error of prediction (SEP) of 1.21 kg/cm^2.

Pork

Pork quality covers inherent properties decisive for the suitability of the meat for further processing and storage including retail display. The main attributes of interest are the water-holding capacity, color, the fat content and composition, oxidative stability, and uniformity (Rosenvold and Andersen, 2003). In addition, pork quality is the result of a complex combination of factors, with interactions among the sensory environment, genotype, and nutritional environment combining with perimortem metabolism to influence final meat quality (Purslow et al., 2008). Pork quality can encompass a combination of factors including taste, appearance, color, leanness, ultimate pH, water-holding capacity, intramuscular fat, nutritional value, wholesomeness, and safety. The quality of fresh pork varies greatly and is traditionally classified into different categories based on color, texture (firmness), and exudation (drip loss) (Warner et al., 1997; Qiao et al., 2007; Kazemi et al., 2009). The preferred method of assessing pork quality is via the direct evaluation of the exposed loin eye at the 10th/11th rib interface of the M. *longissimus* dorsi muscle. Pork meats that are classified as RFN (red or reddish-pink, firm, and non-exudative) have desirable color, firmness, normal water holding capacity, minimal drip loss, and moderate decline rate of pH. In addition, various combinations of color, texture, and drip-loss give other quality grades of pork meat such as RSE (red, soft, and exudative), PFN (pale, firm, and non-exudative), PSE (pale, soft, and exudative), and DFD (dark, firm, and dry). The prediction of pork quality on the slaughter line is not an easy task because some of the biochemical quality properties have not enough time to be fully developed. The evaluation of pork quality should be based on relatively inexpensive and rapid measurements taken in the slaughter line where carcass identification is available in order to have better use of the product for further processing and distribution (Toldrá and Flores, 2000). Application of hyperspectral imaging for direct pork meat quality determination such as drip loss, pH, marbling, texture, and exudation has recently been investigated (Qiao et al., 2005; 2007; 2007a; 2007b).

The research groups of Qiao et al. (2007; 2007a; 2007b) employed a pushbroom hyperspectral imaging system (400-1000 nm) with a complementary metal–oxide–semiconductor (CMOS) camera, a spectrograph, a fiber-optic line light and a conveyor belt controlled by a computer to classify pork to different quality classes and to predict some quality attributes of pork. Qiao et al. (2007) aimed to classify 40 pork samples of four quality grades (RFN, PSE, PFN, and RSE). Spectral data were extracted from a small portion (region of interest) of each sample to represent each quality class, then the data were analyzed using PCA, and the samples were classified by using cluster analysis and artificial neural network (ANN). The results revealed that hyperspectral imaging was able to show the difference in spectral characteristics of the tested four quality levels. In their later study, Qiao et al. (2007a) increased the number of pork samples to 80 steaks and then extracted average spectral features from the whole pork steak instead of a small ROI. As they found in their previous study (Qiao et al., 2007), Qiao et al. (2007a) emphasized that there were spectral differences among the four classes, indicating that there were some differences in their physicochemical attributes. The differences in spectral data suggested a possibility of classifying the quality classes of pork samples using their spectral features. The relevant wavelengths at which the main difference between the pork classes occurred were selected by PCA and stepwise regression. Classification results using these selected wavelengths showed a performance of 67.5 to 87.5% with the best result of 87.5% using the wavelengths selected by PCA experienced in the first derivative spectra.

Qiao et al. (2007b) continued their studies using the same hyperspectral imaging system for predicting drip-loss, pH, and color of pork meat. Simple correlation analysis was conducted between the spectral response at each wavelength and corresponding drip loss, pH, and color, respectively. The simple correlation analyses showed that the highest correlation coefficients (r) were found at 459, 618, 655, 685, 755, and 953 nm for drip loss, at 494, 571, 637, 669, 703, and 978 nm for pH, and at 434, 494, 561, 637, 669, and 703 for color. The results using only spectral data at these wavelengths instead of the whole spectral range showed that the drip loss, pH, and color of pork meat could be predicted with correlation coefficients of 0.77, 0.55, and 0.86, respectively. Such findings represent an obvious advantage for non-contact pork quality determination as pork traits and the softness of the lean pork are more difficult to appreciate from the distance, particularly in the case of the RSE class.

It is well known that all pork meat supplied to the markets must undergo quality controls in order to guarantee consumer safety. Unfortunately, there is still no technology for the rapid, accurate, and non-destructive detection of bacterially spoiled or contaminated meat. The present traditional methods detecting bacterial spoilage in meats, such as enumeration methods based on microscopy, ATP bioluminescence, and the measurement of electrical phenomena, as well as detection methods based on immunological, nucleic acid-based procedures, serological, and molecular approaches are time-consuming, labor-intensive, and give retrospective information. Furthermore, these methods may require special personnel training for sample manipulation, or sample enrichment steps to permit cell recovery and microbial growth before detection (Peng et al., 2009). Because the safety and integrity of the food supply is an important requirement for consumers to ensure superior food quality that is free from hazards, spoilage and/or contamination, Peng and Wang (2008) explored the potential of hyperspectral imaging system based on support vector machines (SVM) for detecting the total viable count (TVC) of bacteria in pork meat. After the hyperspectral reflectance images were acquired and pre-processed, a stepwise discrimination method was then used to determine the optimal wavelengths which can characterize the gross change of TVC on pork meat. Five optimal wavelengths (480, 525, 650, 720, and 765 nm) were found to be accounted for about 94% of the total contribution to TVC prediction. In order to predict the TVC of pork meat, least square support vector machines (LS-SVM) was adopted as the modelling method. The prediction model based on least square support vector machines (LS-SVM) model and the optimal five wavelengths was able to predict TVC with $r = 0.87$ and the results were considerably better than that of artificial neural networks (ANNs) and multilinear regression (MLR) methods. This research demonstrated the feasibility of using the hyperspectral imaging system coupled with LS-SVM model as a valid means for non-destructive determination of the level of spoilage of pork meat.

Chicken

Hyperspectral imaging has been intensively utilized for quality evaluation and monitoring of chicken and poultry products in off-line and on-line applications throughout many research endeavors (Windham et al., 2003; 2005; 2005; Lawrence et al., 2004; Park et al., 2006a; 2006b; 2007; Chao et al., 2008; Yang et al., 2009). The widely conducted research of hyperspectral imaging systems in poultry quality evaluation has been concentrated on the differentiation between wholesome and unwholesome freshly slaughtered chickens, chicken quality classification, and detection of contaminants and tumors in chicken carcasses. Some of the developed hyperspectral imaging systems have already been installed in a real-time inspection line where spectral image is captured for each bird, and the image is then processed by the system's computer to determine whether or not the bird has a disease, a contaminant, or a systemic defect. In addition, the system could also provide some information to detect small birds, broken parts, bruising, tumors, and air sacs. In order to implement hyperspectral imaging for quality control to minimize contaminated carcasses reaching the consumer, each contaminant needs to be identified and classified. The spectral diagnostic system could be used as a non-invasive tool to monitor production line of chicken carcasses by developing spectral profiles from hyperspectral images taken during all stages of production. After developing, calibrating, validating, and testing the hyperspectral imaging system and generating a multispectral imaging system with limited effective wavebands for certain applications in a real-time implementation, the system could be deployed in real processing lines. The proposed system should inspect a huge number of birds in real harsh working environments.

Contamination Detection in Chicken

The hazard is the potential risk of encountering a biological, chemical, or physical agent in food with the potential to cause an adverse health effect. Recently, consumer concerns about the safety of meat products have led to the introduction of legislation to require mandatory inspection of meats and poultry. Consumers want some assurance that the product available for purchase is safe and wholesome. Contamination of poultry with bacterial food-borne pathogens can potentially occur as a result of exposure of the animal carcass to fecal materials during or after slaughter. During the course of slaughter and processing, there are opportunities for the alimentary tract, from crop to colon, to leak or rupture, spilling contents onto the skin or muscle of broiler carcasses. Fecal and ingesta contaminants on poultry carcasses are prohibited due to the potential presence of bacterial pathogens. Microbial pathogens can be transmitted to humans by consumption of contaminated undercooked or mishandled meat and poultry. 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 number of representative samples from a large production run. In addition to being a very tedious task, the manual inspection method is both labor intensive and prone to both human error and inspector-to-inspector variation (Liu et al., 2003b). Without proper inspection protocols during slaughtering and processing, the edible portions of the poultry carcasses can become contaminated with bacteria capable of causing illness in humans. Therefore, regulation emphasized that carcass with visible fecal contamination has to be removed in order to prevent cross-contamination among carcasses. For safety purposes, the identification and separation of poultry carcasses contaminated by feces and/or ingesta are very important to protect the public health from a potential source of food-borne illnesses.

In the area of contamination detection that frequently occurred on the surfaces of poultry carcasses, researchers have developed hyperspectral imaging systems of different designs and sensitivities for the identification of fecal matter and ingesta. The USDA Agricultural Research Service (ARS) is the pioneer research institution for developing hyperspectral and multispectral imaging techniques to detect different contaminants on poultry carcasses. Intensive research has been exerted by USDA 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 application (Park et al., 2002; Lawrence et al., 2003; Liu et al., 2003b).

In detecting contaminants (feces and ingesta) in poultry carcasses, several steps are required, as summarized by Park et al. (2002). First, the spectral data were extracted from normal and contaminated surfaces either by using VIS/NIR spectrometer or from the hyperspectral image itself followed by dimensionality reduction of the hyperspectral data using PCA, followed by the identification of the dominant wavelengths (434, 517, 565, and 628 nm) based on the highest value of PCA loadings and calibration regression coefficients. Band ratios among the selected spectral images at these wavelengths were then calculated and the background noise from the carcasses masked image was removed. Next, some spatial image processing steps such as histogram stretching and filtering were applied to the masked images to visually segregate individual fecal and ingesta contaminants. Effective hyperspectral image processing algorithms, specifically band ratio of dual-wavelength (565/517) images and histogram stretching were finally developed for 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 3 shows visual results of a poultry carcass with the image-processing algorithm applied to a calibrated smoothed pre-processed hyperspectral image. In the ratio images (I_{565}/I_{517}) as shown in Fig. 3c, there was a notable difference in the contrast between the carcass and the background and the contaminant which could be easily detected by employing various threshold values as shown in Fig. 3e. Although a band-ratio of 3-wavelengths (I_{576}-I_{616})/(I_{529}-I_{616}) had some success in contaminant detection as well, a band-ratio image-processing algorithm with 2-bands (I_{565}/I_{517}) performed very well with 96.4% accuracy for detecting both feces (duodenum, ceca, colon) and ingesta contaminants while some false positive pixels were also detected (Park et al., 2006b).

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

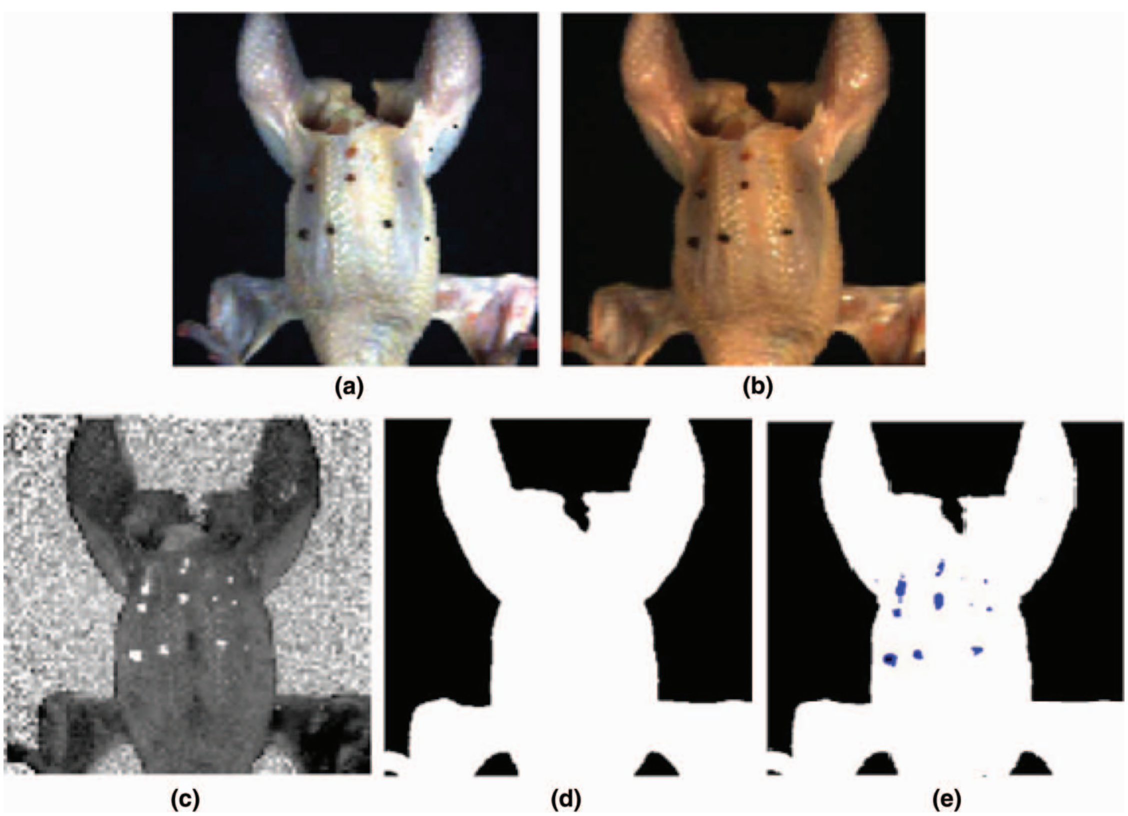

Figure 3 Hyperspectral imaging for detecting contaminations in poultry carcass. (a) color composite image (pseudo-RGB image) showing contaminated spots of feces and ingesta; (b) calibrated color image; (c) band ratio image (I_{565}/I_{517}) with a notable difference in contrast between normal skin of the carcass and the contaminants; (d) background mask; (e) detected contaminants using a threshold of 0.95 with filtering. (color figure available online.)

would act as optimal wavelengths for this purpose. In their earlier work, Windham et al. (2003) extracted the same optimal wavelengths (434, 517, 565, and 628 nm) to detect feces and ingesta on poultry carcasses. Their developed method based on band ratio (especially with a ratio of 565/517 nm) was able to detect 100% of the fecal contaminants in a limited population of broilers. 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 from the upper digestive tract. 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 hyperspectral imaging system was able to detect 100% of the crop and gizzard contents regardless of the mass or spot size. However, not every pixel associated with a given spot was detected.

Lawrence et al. (2004) used a scanning monochrometer that measured the average spectra of uncontaminated skin and fecal and ingesta contaminants and compared this technique to another method using ROI from a hyperspectral image to collect averaged spectra. They reported that both techniques were able to classify contaminated skin from uncontaminated skin with 99% accuracy. However, several regular carcass features were identified as false positives when the classification model developed from the monochrometer spectra was applied to whole-carcass hyperspectral images. A new partial least squares regression model with meat and skin shadow spectra was developed resulting in different principal component loadings with a classification accuracy of 99.5% and fewer false positives. Park et al. (2007) tried to develop a classification method to identify the three typical fecal (duodenum, cecum, and colon) and ingesta contaminants on the carcasses using a spectral angle mapper (SAM) supervised classification algorithm with overall accuracy of 90.13%, and a standard deviation of 5.4%.

Detecting Tumors, Diseases, and Bones

The presence of tumors, diseases, and bones in chicken carcasses represents serious problems to the producers because they are not acceptable at all by the consumers and their detection is a big challenge because most of these blemishes are rather difficult to discern by using the traditional manual inspection. Therefore, some research endeavors using the hyperspectral imaging technique have been accomplished for detecting unwholesome chickens from the wholesome ones especially in production plants (Fletcher and Kong, 2003; Kong, 2003; Kim et al., 2004; Kong et al., 2004; Nakariyakul and Casasent, 2004; 2007b). Tumor is 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, conventional vision-based inspection systems operating in the visual spectrum may suffer limitations in detecting skin tumors on poultry carcasses (Du et al., 2007). In addition, tumors have different spectral responses and some parts of normal chicken skin even have similar spectral response to that of tumors, making their identification a difficult task (Nakariyakul and Casasent, 2004).

Based on the difference between spectral signatures of normal and blemished skins, relationships between some wavebands can further amplify the differences between the two classes. The spectral map defined from spectral analysis is then used as an input to a spatial classification depending on structural properties of the blemishes such as size, filling ratio, and ratio of major to minor axes. In their experiment for detecting tumors in chicken carcasses, Kim et al. (2004) presented a method using hyperspectral fluorescence imaging system; however they failed to detect some tumors that were smaller than 3 mm in diameter. Their resultant detection rate, false positive rate, and missing rate of the proposed method were 76%, 28%, and 24%, respectively. The computational speed of tumor detection can be accelerated by selecting only a few optimal wavebands from hyperspectral data to identify a subset of significant spectral bands in terms of information content and to remove the bands of less importance. For selecting key wavelengths in tumor detection dilemmas, principal component analysis of some regions of interests representing normal and tumor areas provides an efficient mechanism for selecting some narrowband wavelength regions for use in a multispectral imaging system.

As bone fragments embedded in boneless chickens are undesirable by consumers, Yoon et al. (2006; 2008) employed both transmittance and reflectance hyperspectral imaging methods for detecting bone fragments in de-boned chicken fillets. Yoon et al. (2006) used a back-illuminated structured light as a way of reducing the influence of light scattering and increase contrast on images. Later, Yoon et al. (2008) applied an image formation model called illumination-transmittance for correcting nonuniform illumination effects and thus detecting embedded bones easily by segmentation. The results are promising, showing that in conjunction with appropriate image processing algorithms, the hyperspectral imaging system is an effective technique for identifying bones on poultry carcasses.

In disease detection, hyperspectral imaging system was successfully used to differentiate freshly slaughtered chickens from diseased chickens (Yang et al., 2009). Because the ideal inspection regulations require zero tolerance for unwholesome chickens exhibiting symptoms of septicemia or toxemia, these unwholesome chickens must be removed from the processing line. Septicemia is caused by the presence of pathogenic microorganisms or their toxins in the bloodstream, and toxemia results from toxins produced by cells at a localized infection or from the growth of microorganisms. Lu and Chen (1998) acquired hyperspectral images from four classes of poultry carcasses (normal, cadaver, septicemia, and tumor), observing differences in the spectra of the relative reflectance between wholesome and unwholesome carcasses. Also, there were observed differences among the three classes of unwholesome carcasses from their respective spectra. Therefore, 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 of wholesome and systemically diseased chickens, resulting in identification equivalent to that by human inspectors (Chao et al., 2008). The system is installed in poultry processing and inspection plant by acquiring hyperspectral images for 5549 wholesome chicken carcasses and 93 unwholesome chicken carcasses on a commercial processing line. The imaging system inspected over 100,000 chickens on a commercial line during two eight-hour shifts in continuous operation and achieved over 99% accuracy in identifying wholesome chickens and over 96% accuracy in identifying unwholesome chickens. Chao et al. (2008) emphasized that this type of system can perform food safety inspection tasks accurately and with less variation in performance at high speeds, and can help poultry plants to improve production efficiency and satisfy increasing consumer demand for poultry products.

Fish

Evaluation of Fish Overall Quality

The term quality in case of fish refers to the aesthetic appearance and freshness or degree of spoilage which the fish has undergone (Huidobro et al., 2001). It may also involve in safety aspects such as free from harmful bacteria, parasites, or chemicals. Applications of hyperspectral imaging for quality assessment of fish and seafood products are mainly concentrated on overall fish freshness and chemical composition determination. Compared with NIR spectroscopy, applications of hyperspectral imaging in quality evaluation of fish in both research and industry are limited although there is a prevailing tendency of promising success. That is probably because hyperspectral imaging is still a relatively new technique, and its full potential has yet to be exploited. If applied in production and packaging plants, hyperspectral imaging will enable optimized processing of the raw fish, correct pricing, labeling and documentation, and quality authentication.

It is believed that a suitable system for objective analysis of fish freshness would improve the ability to market fish on value and to monitor and manage the freshness of fish in the supply chain to reduce waste.

For determining overall freshness of fish as a main element of fish quality, Chau et al. (2009) employed the hyperspectral imaging system in the near infrared (NIR) and shortwave infrared (SWIR) region of 892–2495 nm for such a task. Instead of evaluating the fish freshness at specific regions on the fish surface as in NIR spectroscopy, hyperspectral imaging evaluates the freshness in all spots (pixels) of the fish surface. The results showed that there was a difference among the mean spectra of a whole fish, the fillet flesh, and belly flap regions of a fillet at several locations of the spectra as indicated in their corresponding spectral curves. These dissimilarities between these spectra are attributed basically to the significant differences between chemical compositions of these parts. Mean spectra for the whole cod fish showed evidence of an increase in reflectance (decrease in log (1/R)) with storage time. Also, many variations in reflectance were observed across the body of the tested fish of different storage time, indicating significant shift of the fish condition and its freshness status.

As with other foods, safety is a critical issue in the fish industry. The fish industry must deliver fish and fish products free from parasites and diseases. Several approaches have been tried to develop an efficient method to detect parasites, but so far, the only reasonable solution is the manual inspection and trimming of each fillet on a candling table. The candling table consists of a bright diffuse light source that is directed to shine through the translucent flesh of the fillet (Valdimarsson et al., 1985). This is a very labor intensive method, where the operator has to inspect the fillet first and then manually remove the defects from the fillet. On the other hand, computer vision systems using only morphological features extracted from digital images have limited performance, because the parasites appear in any shape and are often very similar to the flesh features of the fish fillets. Therefore, it is pertinent to develop a reliable and nondestructive technique for detecting parasites and other illness causing agents. Although it is sometimes invisible to human eyes, parasites and nematodes could be easily detected by hyperspectral imaging technology due to the fact that nematodes in fish flesh presents distinctive spectral fingerprints compared to the normal fish muscles. Wold et al. (2001) and Heia et al. (2007) used a hyperspectral system to detect nematodes in cod (*Gadus morhua*) fish fillets. Their methodology has proven to be an effective one for automatic detection of parasites even at 6 mm (Wold et al., 2001) and 8 mm (Heia et al., 2007) below the fillet surface, which is 2 to 3 mm deeper than what can be found by manual inspection of fish fillets.

In their experiments for detecting parasites in cod fish fillets, Wold et al. (2001) used a multispectral imaging system of different bandwidth and exposure time in the transmittance mode (where the light source is located below the fillet) for detecting parasites impeded in cod fillets on the basis of spectral characteristics in the visible and near infrared region. The length of the tested nematodes spanned from 15 to 40 mm, and the color varied from dark brown, yellow/reddish to almost white. They noticed a significant difference in the spectral properties between parasites at different depth and those of normal flesh. Spectra vary in both intensity and shape, depending on factors such as the color and depth of the parasite, the concentration and depth of the blood spot, and the thickness of the dark muscle. Also, the deep parasite has higher transmittance, resulting in lower contrast compared to white muscle. Image channels in the near-infrared have the potential to "see" deeper than those in the visible area, but the best classification is obtained by combining channels from both regions. The method has potential for online implementation, but further studies are required to verify feasibility for the fish industry.

In another attempt, Heia et al. (2007) used a hyperspectral imaging system in the range 350-950 nm with a spectral resolution of approximately 2 to 3 nm and spatial resolution of 0.5 × 0.5 mm for detecting parasites of different colors and at different depths in cod fish fillets. After extracting spectral data from normal flesh with and without parasites, discriminant partial least squares regression model was used for predicting the presence of parasites in each pixel of the spectral image. Due to distinctive spectral characteristics of nematodes which differ sufficiently from those of fish flesh, fairly good classifications are obtained. In this respect these results are very promising, indicating that instrumental detection may perform better than today's manual procedure. Spectral imaging system as presented in these studies is proven to be feasible in view of the on-line requirements of fish-processing industry.

Recently, Sivertsen et al. (2009) developed a hyperspectral imaging system in transflection mode in which illumination and measurements were performed on the same side of the sample for detecting centerlines of cod fish fillets. Transflection can eliminate the effect of specular reflection, and increase the signal received from inside the sample. The centerline consists mainly of blood remnants in arteries and veins that have been cut off during filleting, which gives the centerline its red/brown color. By using the ratio between 715 nm and 525 nm bands, the centerline could be represented as pixels with high intensities where the surrounding muscle has a lower intensity. A drawback with this method is that not only did it enhance the centerline, but also enhanced all areas of high blood content. The results showed that the centerline can be detected with an average accuracy of 1 mm from the tail and 77% into the fillet relative to its total length, although it was claimed that this method was ready for industrial use with respect to both accuracy and computational requirements.

Compositional Distribution in Fish

Existence of spectral and spatial details together in one spectral image enables demonstrating the product characteristics and attributes, uniformity and quality of the tested product. Since every pixel in the hyperspectral images has its own spectrum, this allows the prediction of component concentration at these pixels, leading to the creation of concentration images to visualize the chemical composition of different components in maps called chemical images (Burger and Geladi, 2006). For detailed food analysis, concentration gradients of certain chemical components are often more interesting than average concentrations, no matter how accurately the latter are determined. With conventional spectroscopy one can either monotonously scan the entire sample point by point or obtain average properties over the entire sample using a single measurement. This is where hyperspectral imaging proves to have superior potential. In some circumstances, selecting one image plane at a particular wavelength in the hyperspectral image can highlight the spatial distribution of sample components, provided that their spectral signatures are different at the selected wavelength. However, only one image at a single wavelength is sometimes not able to show all spatial differences in chemical composition of the sample under investigation because each component has its own spectral features at different wavelengths; in addition, some components have unique spectral features at more than one wavelength. Recently, some research efforts have been directed towards using the hyperspectral imaging technique for determining crude chemical compositional distribution of fish and demonstrating fish quality traits in visualized forms (Wold, et al., 2006; ElMasry and Wold, 2008; Ottestad et al., 2009; Segtnan et al., 2009; 2009).

The first attempt was reported by Wold et al. (2006) for inspecting dried salted coalfish (bacalao) using non-contact transflectance near infrared spectral imaging system in the visible and near infrared regions (460-1040 nm). Fish was put on the conveyor belt and moved at a speed of approximately 0.1 ms^{-1}, and the spectral images were acquired with a spectral resolution of approximately 20 nm at the speed of 10,000 spectra per second. The fish was scanned line-by-line to collect the entire spectral image and the final image size varied according to the length of the fish. The system was evaluated for moisture determination in 70 dried coalfish, which is an extremely heterogeneous product. Partial least square regression (PLSR) was used for making a calibration model between spectral data and reference values of water content. Also, the PLSR model was used to predict water content in each pixel of the spectral image to visualize the water distribution in the tested fish samples. The best prediction models obtained correlation values of 0.92 and RMSECV (root mean square error estimated by cross validation) of 0.7%, which is much more accurate than today's traditional manual grading.

The same system was later used by ElMasry and Wold (2008) in the interactance mode to determine water and fat content distribution in the fillets of six fish species (Atlantic halibut, catfish, cod, mackerel, herring, and saithe) in real time. The resulting chemical images were displayed in colors, where the colors represent different concentrations. Although it is impossible to differentiate the fat and water distribution in the fillet by the naked eye, the spatial distribution of water and fat could be visualized by the NIR interactance imaging system. It was observed that the concentrations of fat and water vary drastically among different parts of the same fillet. This enables early sorting of products and thereby improves quality management. Also, fish manufacturers who wish to cut away fillets with certain threshold concentrations could perform this task easily with limited modification in their production lines.

In another interesting endeavor for compositional distribution application in fish, a spectral imaging technique in interactance mode was also used for non-destructive distributional analysis of fat and salt (NaCl) in salmon fillets during salting, salt equilibration, and smoking, which are considered very crucial for modern fish processing plants. Segtnan et al. (2009) acquired spectral images of salted and smoked salmon fillets and extracted their corresponding average NIR spectra. Calibration models were built between the average NIR spectra and fat and NaCl values using PLSR, and the models were validated using full cross-validation. The NIR prediction model

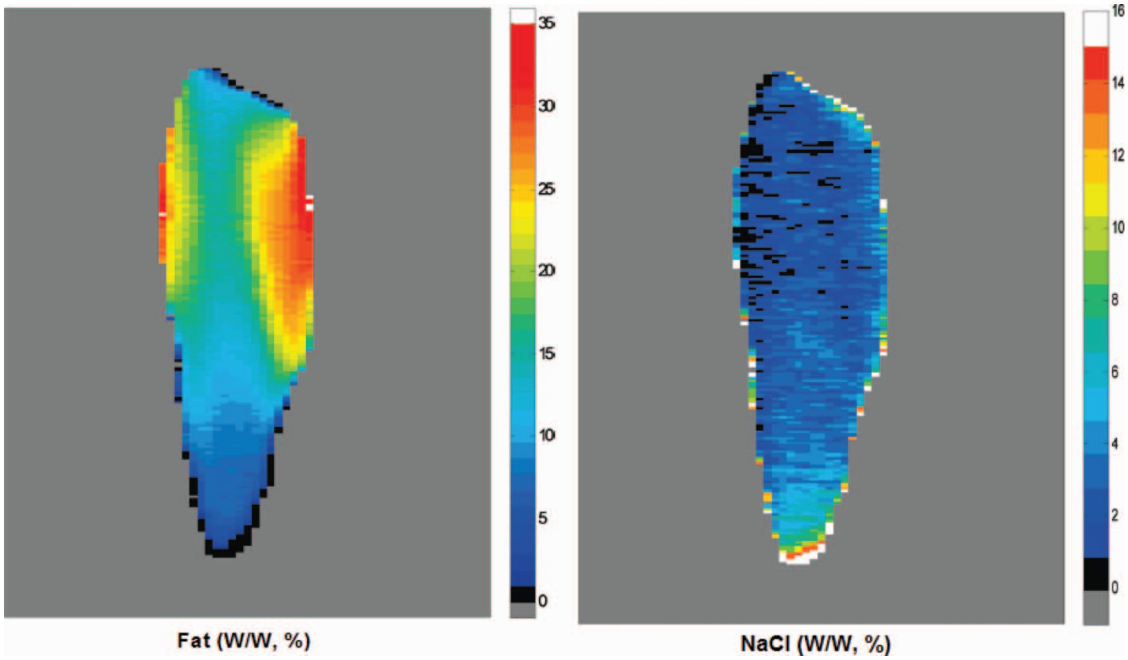

Figure 4 Predicted chemical images for fat (left) and NaCl (right) using NIR interactance imaging (Segtnan et al., 2009). (color figure available online.)

gave an RMSECV of 0.56 and a correlation of 0.86 for the NaCl content and prediction errors of 1.95 and 1.96% fat in raw and salted salmon fillets, respectively, with corresponding correlations between predicted fat values and reference values of 0.95 and 0.97. Examples of fat and NaCl prediction images obtained using NIR interactance models are shown in Fig. 4. From the industrial point of view, this NIR interactance system could be a good choice of technique, as it is able to measure fat and NaCl simultaneously.

LIMITATIONS OF HYPERSPECTRAL IMAGING IN MEAT APPLICATIONS

Despite these interesting and excellent research efforts which clearly reflect the great value of hyperspectral imaging techniques in meat quality evaluation, the system is suffering from some constraints which limit its full exploitation. Some difficulties arise from the hardware capability needed for an efficient and rapid scanning to acquire the whole image and the subsequent analysis of the high amount of data produced. The main problem associated with hyperspectral imaging system is that it produces spectral images of substantial amount of data with redundant information known as multicolinearity problem which poses considerable computational challenges. This makes hyperspectral imaging difficult to be implemented in on-line inspection of meat or other agricultural products where rapid data processing is essential, and represents a particular challenge to equipment designers. The problem for the implementation of on-line applications due to the big size of hyperspectral images requires efficient programming tools for handling, displaying, visualizing, and processing such images in a real-time mode. Therefore, with such a high amount of raw data produced per image, hyperspectral systems are currently used off-line in the laboratory to select some key wavelengths for building multispectral imaging systems suitable for on-line applications to meet the speed requirement of real-time production lines (Chao et al., 2002; Mehl et al., 2004). In this aspect, reducing the dimensionality of hyperspectral images is advantageous in the sense of improving the predictability of the calibration model and simplifying the model by avoiding redundancies and irrelevant variables. However, it can be expected that future developments in system components and more robust and efficient algorithms will reduce acquisition and processing time, enabling real-time applications with higher spectral resolutions. On the other hand, one of the main analytical drawbacks of hyperspectral imaging technique is that it is an indirect method which means that it needs standardized calibration and model transfer procedures. Also, hyperspectral imaging is not suitable in case of homogenous samples because the value of imaging lies in the ability to resolve spatial heterogeneities in samples. Furthermore, sample movement during image acquisition can cause unwanted spectral artifacts when heterogeneous samples are analyzed. However, by considering a wide range of meat properties during establishing calibration models, it will definitely enhance the predictability of these models for a wide range of quality and safety testing practices in the meat industry for different meat quality traits. Another constraint compared with the other technologies is the high initial cost of hyperspectral imaging systems; however, this is expected to be a minor barrier in the forthcoming years because the increase of commercial suppliers could reduce the cost and improve its availability. Future improvements in equipment and software and the development of novel solutions for more powerful data acquisition and image processing are likely to decrease costs and increase applications of this emerging technique for meat quality evaluation and characterization.

FUTURE TRENDS

The results of previous research works presented in this review confirmed that hyperspectral methods are well suited for predicting essential properties in meat samples such as tenderness, pH, and water holding capacity, and mapping the spatial distribution of chemical components in different meat products. It can replace computer vision or spectroscopy in situations where more accurate classification, sorting, or identification of foods and agricultural products is required. Hyperspectral imaging techniques may find applications in the meat industry for simple product inspection, full sample quantification, or for the segregation of a subset of the measured batch for further manual inspection. Considering the high spectral resolution of hyperspectral images used in recent studies, deeper research is required to extract the useful information and reject the voluminous data that do not contribute to the application.

By integrating with efficient chemometric multivariate data processing techniques and better configurations, hyperspectral imaging techniques open many interesting perspectives for both qualitative and quantitative analysis in food processing in general and meat industry in particular. The non-destructive, remote, and multivariate characteristics of hyperspectral imaging techniques provide an interesting platform for meat quality monitoring and control to move the measurements of meat quality from the laboratories to the processing lines. Indeed, there are some industrial approaches leaning in this direction, although they have not yet been fully exploited, due to limitations and restrictions explained above. As a result, it is expected that the hyperspectral system will prevail in the near future for more complex applications in monitoring different stages of most meat processing plants. Also, the abundant information characterizing both chemical and morphological features laid in the spectral images opens the way to build chemical images to visualize and quantify the spatial distribution of the functional components of meat products during their processing. This particular feature will enable implementing some difficult applications such as fraud detection of processed meat products; authentication of superior meat quality; detection of various defects and diseases; discrimination between different meat qualities; uniformity distribution of chemical compositions; and monitoring the overall quality. The accurate classification of different quality grades based on these characters will be very important for correct pricing, authentication, and categorization of meat products which provides some economical benefits for producers by increasing consumer confidence in the supplied meat products.

CONCLUSION

This review has covered some of the recent applications of hyperspectral imaging systems in meat quality evaluation. As a rapid and non-invasive technique, hyperspectral imaging has already gained wide acceptance among researchers as a competent tool for non-destructive evaluation of meat products. In support of greater regulatory inspection and consistent with the food industry's goal of providing superior meat quality, hyperspectral imaging systems greatly enhance the knowledge and understanding of product parameters along the production process. Among the numerous techniques which have been proposed for meat quality evaluation on the fresh intact form, hyperspectral imaging technique has great potentials. The main advantage of this technique is that it is a chemical-free assessment method where sample preparation is eliminated and thus reduces time for analysis and eliminates expensive traditional methods. The wide application of this automated system would seem to offer a number of potential advantages, including reduced labor costs, elimination of human error during subjective judgment, and the creation of product data in visualized forms in a real time for documentation, traceability, and labelling. In contrast to NIR spectroscopic and imaging techniques, hyperspectral imaging offers a full range of spectral measurements combined with spatial properties. However, it is necessary for researchers to overcome technological limitations for implementing hyperspectral imaging in the food industry for meat quality assessment, so that the meat industry can realistically benefit from the possibility of performing this non-destructive technique at an early stage of processing without additional laborious and time-consuming chemical analyses, enabling early sorting of produce and thereby improved quality management. Considering the continuing improvements in hardware and software design and the analytical requirements of the most recent concepts of quality, it is anticipated that hyperspectral imaging may progressively become a routine method for meat process monitoring and for food safety and quality control.

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