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Review

Recent developments of hyperspectral imaging systems and their applications in detecting quality attributes of red meats: A review

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A B S T R A C T

Red meats, such as pork, beef, and lamb meats, play an important role in people's daily diet as they can provide good protein, vitamins, and minerals to promote human health. Either the meat processing industry or consumers usually evaluate meat quality with some common quality characteristics, which generally encompass microbiological attributes (freshness, spoilage), chemical attributes (fat, protein, moisture), sensory attributes (color, tenderness, flavor) as well as technological attributes (pH, water-holding capability). Manual inspection and chemical detection methods are tedious, time-consuming, and destructive. Consequently, fast and nondestructive methods are required for detecting these attributes in the modern meat industry. Hyperspectral imaging is one of the promising methods, which integrates the merits of imaging and spectroscopy techniques. This paper provides a comprehensive review on the recent development of hyperspectral imaging systems and their applications in detecting some important quality attributes of pork (color, drip loss, pH, marbling, tenderness, chemical compositions), beef (color, pH, tenderness, water-holding capacity, microbial spoilage), as well as lamb (color, drip loss, pH, tenderness, chemical composition). Finally, the future potential of hyperspectral imaging is also discussed.

Contents

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1. Introduction

Red meats are a significant part of people's daily diet as they can provide good protein, vitamins, and minerals to promote human health (McAfee et al., 2010). Among a variety of red meats, pork, beef and lamb are commonly served as people's first-choice sources of animal protein. With the improvement in living standards, people currently pay more attention to the quality of food products. Therefore in the modern agri-food industry, quality is one of the most important concerns and the industry is always looking for new technologies such as novel cooling (Sun and Brosnan, 1999; Sun and Zheng, 2006; Sun and Hu, 2003; Wang and Sun, 2001), freezing (Delgado et al., 2009; Zheng and Sun, 2006), drying (Sun, 1999; Sun and Byrne, 1998; Sun and Woods, 1993, 1994a, 1994b, 1997; Cui et al., 2004) and edible coating (Xu et al., 2001) to enhance product qualities. For meat products, how to keep them in high quality is critical as high quality products are the basis for success in today's highly competitive market. Therefore, the meat industry should manufacture superior red meats to fulfill consumers' expectation so that they can dominate the market better. Meat quality is usually defined as a measurement of attributes or characters that determine the suitability of meat to be eaten as fresh or stored for reasonable period without deterioration (ElMasry et al., 2012a). Furthermore, meat quality attributes could encompass chemical attributes, microbiological attributes, sensory attributes and technological attributes (Mancini and Hunt, 2005; Chen and Qin, 2008; Rosenvold and Andersen, 2003; Otto et al., 2004; Andrés et al., 2008; Warner et al., 1997; Agullo et al., 1990; Pathare et al., 2013), as illustrated in Fig. 1. These attributes highly affect the quality of red meats because of the great variability in these attributes, which results from a direct integration of conditions such as pre-slaughter, stunning method, and electrical stimulation. Particularly, this issue will be aggravated if the industry is unable to characterize this level of quality satisfactorily. Traditionally, sensory attributes (color, flavor, firmness, marbling, tenderness, etc.) of many foods (Chen and Qin, 2008; Rosenvold and Andersen, 2003; Otto et al., 2004; Andrés et al., 2008; Hernández et al., 2008a, 2008b), including red meats, are inspected by some well trained assessors. In some abattoirs, tenderness is evaluated using a "finger method", and for meat color and marbling, the evaluation methods are similar and are usually carried out by comparing the color of the rib eye muscle (*Musculus longissimus dorsi*) or the proportion of intramuscular fat within the *M. longissimus dorsi* and scored against the reference standards specific for each of the meat species. However, manual inspection is subjective, tedious, time-consuming and inconsistent. In addition, some important internal quality attributes such as acidity and nutritional constituents cannot be detected by manual inspection.

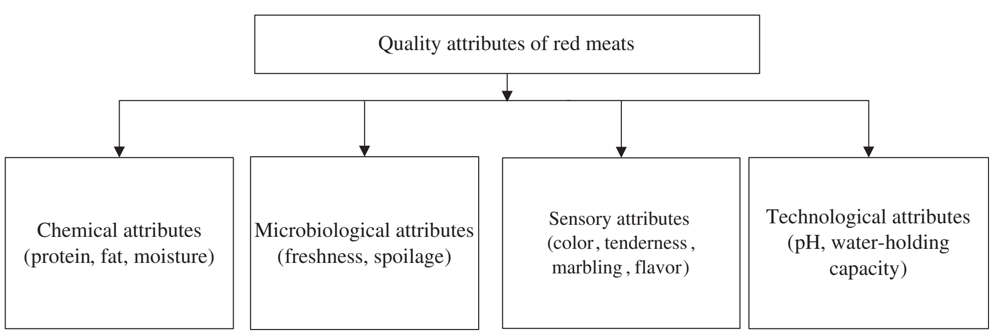

Fig. 1. Common quality attributes of red meats.

Table 1
Comparison of computer vision, spectroscopy, hyperspectral imaging, ultrasound and CT scanning.

Methods	Advantages	Disadvantages
Ultrasound technique	Rapid Non-polluting High sensitivity	Easily affected by operators, measurement sites as well as the ultrasonic frequency Only detecting chemical compositions for some specific parts
CT scanning	Non-invasive Providing detailed images	Expensive Longer evaluation time Limited range of application
Computer vision	Providing spatial information Higher accuracy than manual inspection Able to detect external attributes	Limited multi-constituent information Unable to detect internal attributes
Spectroscopy technique	Simple Providing spectral information Able to detect internal attributes	Limited sensitivity to minor components and complicated analysis
Hyperspectral imaging	Providing spatial and spectral information Sensitive to minor components Building chemical images	High cost Problems of data processing

Besides the manual inspection, other methods like chemical methods and instrumental techniques have been used in detecting quality attributes for a long time, which are more convenient and effective than manual inspection. For chemical methods, the long-time standard for protein analysis is the Kjeldahl method (Petracci and Baeza, 2011), and the method of choice for official fat analyses is a solvent-based method for measuring the total fat content in meat (Petracci and Baeza, 2011). In terms of instrumental methods, pH is traditionally measured by pH meter by inserting it into the muscle directly after incision of the muscle, and colorimeters are commonly utilized for meat color evaluation. In addition, common physical measurement of meat tenderness is based on a Warner–Bratzler shear force (WBSF) or slice shear force (SSF). However, most of the above-mentioned techniques are destructive, tedious, time-consuming and require lengthy sample preparation. Therefore, these methods are not suitable for fast analysis and early detection of quality attributes in industrial and commercial processing. Objective and automatic technologies for detecting these quality attributes are thus being sought by the industry.

In recent years, there have been many research efforts in developing nondestructive techniques (Defraeye et al., 2013; Zhang et al., 2013; Lu et al., 2012; Abdel-Nour et al., 2011; Sowoidnich et al., 2010; Manickavasagan et al., 2010; Zaïdi et al., 2008) for detecting internal and/or external quality attributes. Different techniques based on different principles, procedures, and instruments are currently available for measuring different meat quality attributes. Table 1 shows the comparison of several important non-destructive techniques. Ultrasound technology is one of these non-destructive methods which can be used to determine the physicochemical properties of many foods. Particularly, ultrasound technology has been successfully used for composition measurement in beef (Lambe et al., 2010), lamb (Sahin et al., 2008; Orman et al., 2008) and pork (Gresham et al., 1992). Besides, computed tomography (CT) scanning is another non-invasive method that uses X-rays to create pictures of cross-sections of the body (Prieto et al., 2010). However, CT is considered as an expensive tool, which is mainly used in the field of medicine and the carcass evaluation time is a bit higher than that of other online methods (Kongsro et al., 2009; Font-i-Furnols et al., 2013). Moreover, imaging and spectroscopic techniques, which can provide useful information, are two valuable technologies in measuring meat quality attributes. In the past 20 years, many studies have been reported on predicting quality attributes of red meats using spectroscopic techniques (Prevolnik et al., 2010; Rødbotten et al., 2000; Geesink et al., 2003), especially in near-infrared (740–2500 nm) region. Compared to classical chemical and physical analytical methods, spectroscopic techniques have two apparent advantages (Valous et al., 2010). On one hand, they have a short measuring time with limited sample preparation. On the other hand, they are chemical-free, and can be applied to estimate more than one attribute at the same time. Consequently, spectroscopic techniques have been intensively applied in quality evaluation of pork, beef and lamb (Prevolnik et al., 2010; Rødbotten et al., 2000; Geesink et al., 2003). Unfortunately, conventional spectroscopic techniques alone are not able to provide compositional gradients because the measurement focuses only on a relatively small part of the specimen being analyzed to produce average values of composition. Imaging techniques in the form of computer or machine vision mostly use reflectance mode to detect external quality characteristics such as color, size, shape and surface texture (Jackman et al., 2008, 2011; Du and Sun, 2005; Valous et al., 2009). Imaging techniques can provide superior spatial information and thus have been applied for visual evaluation of red meats for rapidly identifying different quality parameters on the processing line with minimum human intervention. Although external attributes can be easily evaluated by imaging techniques, the techniques are unable to detect compositional attributes such as moisture, fat and protein content due to very limited spectral information.

As a logic extension of both spectroscopy and digital imaging or computer vision techniques, hyperspectral imaging has been

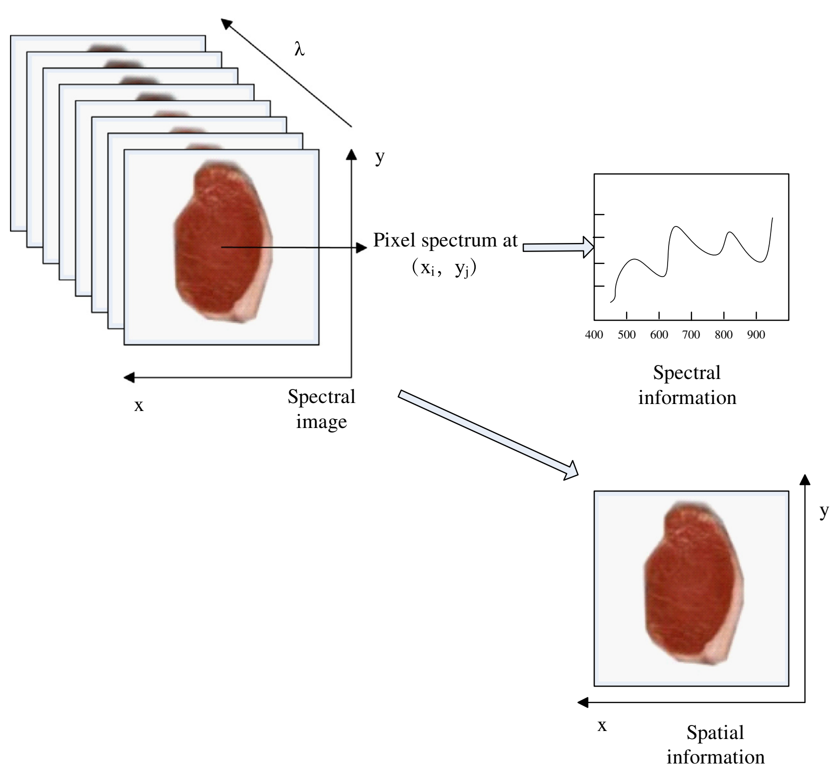

Fig. 2. Schematic illustration of hyperspectral imaging cube.

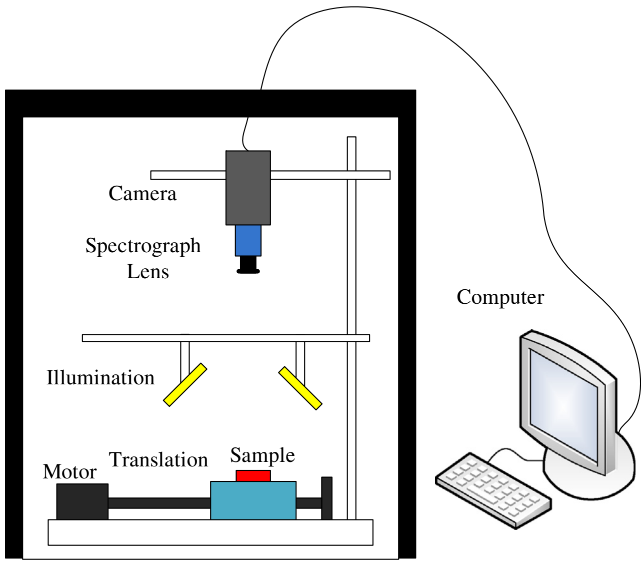

Fig. 3. Components of a typical hyperspectral imaging system.

widely accepted as a new inspiring technique for rapid, reagent-less and nondestructive quantitative applications in the meat industry (Barbin et al., 2012a; Kamruzzaman et al., 2011, 2012a). Compared to conventional spectroscopic techniques, the hyperspectral imaging has advantages of receiving spatially distributed spectral responses at each pixel of a meat image. Such information forms a three-dimensional data cube called "hypercube", which contains two-dimensional spatial information (x, y) as well as one-dimensional spectral information λ_i ($i = 0, 1, \ldots, L-1$) (Wu et al., 2012a). For a fixed λ_k, $I(x, y, \lambda_k)$ represents the kth single-band image (Feng and Sun, 2012). If x and y are fixed, then $I(x, y, \lambda_i)$ stands for the spectrum or spectral information. These data provide a large amount of information that can be analyzed to ascertain minor and/or subtle physical and chemical features in a sample. Fig. 2 demonstrates a schematic representation of hyperspectral imaging hypercube showing the relationship between spectral and spatial dimensions. As the quantitative assessment of physical and chemical attributes is quite important, the distribution of such attributes is extremely significant to fully characterize red meats. Hyperspectral imaging would be suitable for achieving this goal because of its capability of acquiring hundreds of spectra with high spectral and spatial resolution for providing both spectral and spatial information of each pixel over certain wavelength range. In fact, a significant amount of research has been done in the area of hyperspectral imaging applied specially to red meats analysis, highlighting its ability to predict different quality parameters including water holding capacity, pH, color, tenderness and fat content in beef, pork and lamb (ElMasry et al., 2013; Naganathan et al., 2008; Kamruzzaman et al., 2012b, 2013; Barbin et al., 2012b; Qiao et al., 2007a). In order to obtain a broad application, developing hyperspectral imaging systems to assess quality attributes of red meats and to ensure their authentication is important, which would bring economic benefits to the industry. However, there are still some challenges ahead due to high dimensionality and time constraints for image acquisition and subsequent image analyses. Therefore, seeking the most sensitive wavebands so that multispectral imaging systems can be built will be the trend in research and development of the technology.

2. Recent developments of hyperspectral imaging systems

Originally, hyperspectral imaging was developed for remote sensing applications, which utilize satellite imaging data of the earth, moon, and planets, but has since found its potential in other fields like agriculture, pharmaceuticals and the food industry (ElMasry et al., 2012b). In short, hyperspectral imaging systems are mainly made up of two parts: hardware and software. The role of hardware is to obtain the images while software is to process the images in order to extract useful image information for predicting quality attributes of products. With the advancement of science and technology, hardware of hyperspectral imaging systems has become increasingly sophisticated. Meanwhile, software has more powerful capacity for data analysis as well as image processing. Therefore, recent progress of hardware and software development of hyperspectral imaging systems was investigated.

2.1. Advances in hardware

With the fast development of technology, hardware updates at a rather rapid speed and the cost of hardware decreases correspondingly. Fig. 3 shows a typical hyperspectral imaging system, which consists of five components: an illumination unit, a spectrograph, a high performance camera with charge coupled device (CCD) or complementary metal oxide semiconductor (CMOS) sensors, a translation stage operated by a stepper motor and a computer equipped with image acquisition software (ElMasry et al., 2012a).

The illumination unit generates light which illuminates the sample. This part is important because it makes a significant impact on the performance and reliability of the system. Tungsten-halogen lamps, which add halogen elements (F, Cl, Br, I) into quartz tubes, are widely used as illuminators in hyperspectral imaging systems (Buschmann et al., 2005). Compare to normal light bulbs, tungsten-halogen lamps have higher luminous efficiency. Furthermore, halogen frequency can guarantee sustained glow and long lifetime, which is four times more than normal light bulbs. Meanwhile, the long lifetime makes their replacement cycle longer, resulting in substantial cost savings. In addition, other kinds of durable lamps such as HgAr lamps or LED source have been applied as well (Park et al., 2006).

The spectrograph is the most important part of the hyperspectral imaging systems, which helps in generating a spectrum for each point on the scanned line. With the development of sensor technology, many different types of sensors have been developed, which can acquire images in different spatial resolution, temporal resolution and spectral resolution. Imaging spectrographs are gradually developed under this background. According to the characteristics of imaging spectrographs, hyperspectral imagers can be divided into three types: whiskbroom, pushbroom, and tunable filter. Among them, whiskbroom and pushbroom are both spectral scanning methods. The biggest difference between them is that whiskbroom scans the sample in the spatial domain by moving the sample point-by-point while pushbroom is moving the sample line by line. Pushbroom is the most widely used in detecting quality attributes of red meats. On the other hand, tunable filter obtains images one wavelength after another, thus it is also called wavelength scanning. This method is different from the other two ways, as it keeps the meat sample fixed.

The camera is a two-dimensional detector with high performance sensors, which can collect the spectral and spatial information simultaneously. CCD or CMOS are two widely used image sensors that have been developed rapidly in recent years (Litwiller, 2001). CCD is a kind of subminiature image sensor, which uses electric charges as signal carrier. Its working principles are based on light absorption of silicon and photoelectron collection. Now, CCD is one of the most important image sensors because of its high pixel count, high sensitivity, wide spectrum response, high integration, easy maintenance, low cost, and commercial availability. Currently, there have been several recent advances in the application of CCD. On one hand, some improvements have been done on the basis of original structures. For example, frame-transfer CCD (FT-CCD) has been developed to reduce production cost and to improve the device performance (Fife et al., 2007). Furthermore, some researchers developed a low-power imaging system by combining CCD technology with CMOS technology (Suntharalingam et al., 2000). In addition, readout noise of CCD has been reduced by enlarging the gain of amplifiers as well as the gate capacitance. On the other hand, a few novel concepts and methods have been presented to improve the performance of CCD. For example, a new CCD with the capacity of charge storage and slash transfer has been proposed in order to promote the response rate (Aiqun et al., 2007). In terms of CMOS, it is integrated in the semiconductor materials, which are known as metal oxide. The principle of CMOS is to utilize light-sensitive diode for achieving photoelectric conversion (Bigas et al., 2006). Currently, CMOS image sensors are becoming competitive with regard to CCD technology as they own some specific advantages, such as lower power consumption, lower voltage operation, on-chip functionality and lower cost. CCD technology will continue to dominate the high-performance branch, but the performance of CMOS image sensors will continue to improve until the line between CCD and CMOS image quality is blurred. The spectrograph, camera and illumination conditions determined the spectral range of the system. The progress of optical grating technology has resulted in more precise spectral ranges in practical applications (Feng and Sun, 2012).

Finally, the translation stage is used to move the sample past the objective lens so that the entire surface of the sample can be scanned and the computer plays a role in controlling the motor speed, exposure time, binning mode, wavelength range and image acquisition. The enhancement of computers' memory, hard disk capacity as well as the processor makes data storage and data processing become much easier.

In future, hyperspectral hardware, in particular for optical devices, will be more intelligent due to the increasing development of computer techniques, which makes operational control automatic and intelligent. According to the requirements of energy conservation and environmental protection, hardware will move towards lower power consumption and more reliability. In addition, with the rapid development of various disciplines and applications of new materials, more powerful optical elements such as fiber optic sensors will emerge. Fiber optic sensors have attracted the attention of researchers due to their unique properties: small size, light weight, low cost, and strong anti-interference capability (Martellucci et al., 2002). Therefore, fiber optic sensors can simplify devices. Nowadays, many kinds of fiber optic sensors have been developed such as Bragg grating optical sensors, fiber optic Febry–Perot temperature sensors and intensity modulated sensors (Ciziri and Dogan, 2013), and have been widely used for structural sensing and monitoring in civil engineering, aerospace, and medicine (Méndez and Csipkes, 2013).

2.2. Advances in software

Software includes the skills, knowledge and capacity that need to be built up in order to make the transfer of the technology successful. Development of hyperspectral data processing technologies are relatively lagging behind that of hardware. However, due to the great advantages of hyperspectral data, research efforts are intensified to solve some specific problems, such as dimensionality reduction and algorithm exploitation. Furthermore, some high practical software for hyperspectral image processing has been widely applied, including ENVI, MATLAB and others (Mehl et al., 2004; Lu, 2003). ENVI contains the main functions for hyperspectral image analysis, including calibration, filtering, and spectral data extraction in regions of interest (ROI) (Shippert, 2003). MATLAB is powerful in the aspects of algorithm exploitation, data visualization, data analysis, and numeric computation. New versions of MATLAB have added many new powerful toolboxes, such as Parallel Computing Tool, which greatly improve data processing capacity and efficiency (Choy and Edelman, 2005).

Advances in software mainly focus on developing new algorithms for hyperspectral data processing. On one hand, some new methods for dimensionality reduction are developed. There exists high correlation and redundancy among spectral bands of hyperspectral images. Selecting desired bands to achieve dimensionality reduction would not have much impact on the results, but have great practical significance for removing redundant information since it can not only save time but also accelerate data processing. To make full use of hyperspectral images, developing applicable band selection methods is the future direction. Generally, principal component analysis (PCA) and factor analysis (FA) are two widely used linear approaches for feature extraction (Lavanya and Sanjeevi, 2013). Nowadays, some improved band selection algorithms have been proposed, including successive projection algorithm (SPA), principal factor analysis (PFA) as well as independent component analysis (ICA) (Fodor, 2002). In particular, SPA, a forward selection method that uses simple operations in a vector space to minimize variable collinearity, is proposed as a novel variable selection strategy for multivariate calibration (Zhang et al., 2008). In addition, some non-linear selection algorithms such as stimulated annealing (SA), genetic algorithm (GA) and particle swarm optimization are proposed (ElMasry et al., 2012b, 2012c; Feng and Sun, 2012; Liu et al., 2014) to make up the shortage of linear methods. For example, GA, which mimics the natural evolution and genetic mechanisms, is a suitable method for selecting optimum wavelengths and can produce more interpretable results after suitable modifications. This method was originally proposed by Holland (Jones and Rawlins, 1993), and its basic principle is to use a series of operations mainly including selection, exchange, and mutation to keep the optimum variables retained and weed out the poor ones during the process of continuous genetic iteration. On the other hand, some new spectral preprocessing methods such as wavelet transformation (WT), mean sample residual spectrum correction (MSRSC), convolution transform (CT) and orthogonal signal correction (OSC) are developed to reduce or eradicate undesired effects such as light scattering and random noise resulting from variable physical sample properties or instrumental effects (Bruce et al., 2002). These methods are promising, in particular for WT, which performs well in data compression. Classical spectral preprocessing methods mainly includes first and second derivatives, baseline offset correction, de-trending, multiplicative scatter correction (MSC) and standard normal variate (SNV) transformation (Jorgensen, 2000). However, the capability of baseline offset correction is weak due to simple baseline shift. Derivative methods can remove overlapping peaks and correct the baseline, but they are prone to magnify the noise and increase the complexity of the spectrum. MSC is mainly used to eliminate the light scatter influence, which results from the heterogeneity of samples. The principle of MSC is to make the scatter level of all spectra closed to the level of the average spectrum. This procedure is actually to establish a linear relationship between all spectra of a group of samples and the average spectrum, but in some cases, light scatter influence resulting from the heterogeneity of samples is non-linear and MSC does not perform well for eliminating non-linear scatter effect. To a certain extent, new spectral preprocessing methods are able to solve these problems. In specific applications, different preprocessing methods should be selected according to different analysis purposes in order to obtain the best results. If the results are unsatisfactory with only one preprocessing method, it is a feasible plan to combine several different preprocessing methods (Rinnan et al., 2009). With the advancement of hyperspectral

Table 2
Applications of hyperspectral imaging technology in predicting quality attributes of red meats.

Products	Quality attributes	Mode	Spectral range (nm)	Data analysis	Accuracy	Reference
Pork	Protein content	R	900–1700	PLSR	0.92	Barbin et al. (2012b)
	Moisture content	R	900–1700	PLSR	0.87	Barbin et al. (2012b)
	Fat content	R	900–1700	PLSR	0.95	Barbin et al. (2012b)
	TVC	R	400–1100	MLR, PLSR	0.886, 0.863	Wang and Zhang (2010a)
	TVC	R	400–1100	LS-SVM	0.9236	Wang et al. (2011)
	TVC	R	400–1100	LS-SVM	0.942	Wang and Zhang (2010b)
	TVC	R	400–1100	PLSR	0.945, 0.918, 0.919, 0.935	Peng et al. (2010)
	Escherichia coli	S	400–1100	MLR	0.877, 0.841	Tao et al. (2012)
	TVB-N	S	400–1100	PLSR	0.90	Li et al. (2011a)
	Tenderness	S	400–1100	MLR	0.831, 0.860, 0.856, 0.930	Tao et al. (2012)
	Color	R	900–1700	PLSR	0.93	Barbin et al. (2012c)
	Color	R	400–1000	FNN	0.86	Qiao et al. (2007a)
	pH	R	900–1700	PLSR	0.87	Barbin et al. (2012c)
	pH	R	400–1000	FNN	0.55	Qiao et al. (2007a)
	pH	R	400–1100	FNN	0.67	Qiao et al. (2005)
	Drip loss	R	900–1700	PLSR	0.83	Barbin et al. (2012c)
	Drip loss	R	400–1000	FNN	0.77	Qiao et al. (2007a)
	Drip loss	R	400–1100	FNN	0.80	Qiao et al. (2005)
	Marbling level	R	430–1000	FNN	0.75–0.85	Qiao et al. (2007b)
Beef	Protein content	R	900–1700	PLSR	0.86	ElMasry et al. (2013)
	Moisture content	R	900–1700	PLSR	0.89	ElMasry et al. (2013)
	Fat content	R	900–1700	PLSR	0.84	ElMasry et al. (2013)
	Fat content	R	1000–2300	PLSR	0.90	Kobayashi et al. (2010)
	Fatty acid	R	1000–2300	PLSR	0.87, 0.89	Kobayashi et al. (2010)
	TVC	S	400–1100	MLR	0.96	Peng et al. (2009)
	Tenderness	R	400–1000	CDA	0.96	Naganathan et al. (2008)
	Tenderness	S	400–1100	MLR	0.91	Wu et al. (2012b)
	Tenderness	R	900–1700	CDA	0.77	Li et al. (2011b)
	Tenderness	S	496–1036		0.67	Cluff et al. (2008)
	Tenderness	S	400–1100	MLR	0.86	Wu et al. (2010)
	Tenderness	R	900–1700	PLSR	0.83	ElMasry et al. (2012c)
	Color	S	400–1100	MLR	0.92, 0.90, 0.88	Wu et al. (2010)
	Color	R	900–1700	PLSR	0.88, 0.81	ElMasry et al. (2012c)
	Color	S	400–1100	MLR	0.96, 0.96, 0.97	Wu et al. (2012b)
	pH	S	400–1100	MLR	0.86	Wu et al. (2010)
	pH	R	900–1700	PLSR	0.73	ElMasry et al. (2012c)
	WHC	R	890–1750	PLSR	0.87	ElMasry et al. (2011)
	Marbling level	S	400–1100	MLR	0.92	Li et al. (2011b)
Lamb	Protein content	R	900–1700	PLSR	0.86	Kamruzzaman et al. (2012b)
	Moisture content	R	900–1700	PLSR	0.89	Kamruzzaman et al. (2012b)
	Fat content	R	900–1700	PLSR	0.84	Kamruzzaman et al. (2012b)
	Color	R	900–1700	PLSR	0.91	Kamruzzaman et al. (2012c)
	pH	R	900–1700	PLSR	0.65	Kamruzzaman et al. (2012c)
	Drip loss	R	900–1700	PLSR	0.77	Kamruzzaman et al. (2012c)
	Tenderness	R	900–1700	PLSR	0.84	Kamruzzaman et al. (2013)

TVC: total viable count, WHC: water holding capability, TVB-N: total volatile basic-nitrogen; R: reflectance, S: scattering; PLSR: partial least square regression, MLR: multiple linear regression, LS-SVM: least squares support vector machine, FNN: fuzzy neural network, CDA: canonical discriminant analysis.

imaging, more and more spectral preprocessing methods will be developed. In the meantime, the availability of better preprocessing methods appears to accelerate the further development of hyperspectral imaging. Although research on spectral preprocessing has been intensified, derivative processing, MSC and SNV are still commonly used because these algorithms have already been available in commercial software such as Unscrambler while new algorithms have not yet been applied. Therefore, the future trend in exploiting and utilizing novel preprocessing methods is to develop the latest algorithms into simple and practical software so that researchers can use them easily. In addition, methods for establishing more robust models make progress as well. In general, multivariate chemometrics used to establish calibration or prediction models, can be divided into quantitative analysis with multivariate regression and qualitative analysis with multivariate classification (Lorente et al., 2012). Currently, the most widely used multivariate regression methods in quantitative analysis includes PCR (principal component regression), PLSR (partial least square regression), and MLR (multiple linear regression). Based on these linear methods, some modified algorithms such as interval-PLS (iPLS) (Norgaard et al., 2000), which can identify a spectral interval that is especially informative with respect to the parameter under consideration, have been developed to simplify the model and promote its predictive accuracy (Magwaza et al., 2012). Although these linear approaches are promising, unsatisfactory results may be produced when non-linearity is present. Consequently, non-linear methods such as ANN (artificial neural networks), SAM (spectral angle mapper) and SVM (support vector machine) regression have been developed for modeling non-linearity. ANNs are commonly used for modeling non-linearity with some advantages of flexible learning algorithm, diverse network topology, fast learning algorithm and high error tolerance. SVM is another non-linear method that makes input X mapped onto an m-dimensional feature space using some fixed (nonlinear) mapping, and then constructs a linear model in this feature space (Cortes and Vapnik, 1995). Furthermore, optimized versions based on the standard SVM such as least squares support vector machine (LS-SVM) are also developed (Suykens and Vandewalle, 1999). In addition, recent studies showed that combining one multivariate method with another is practical in order to improve prediction accuracy. For example, some

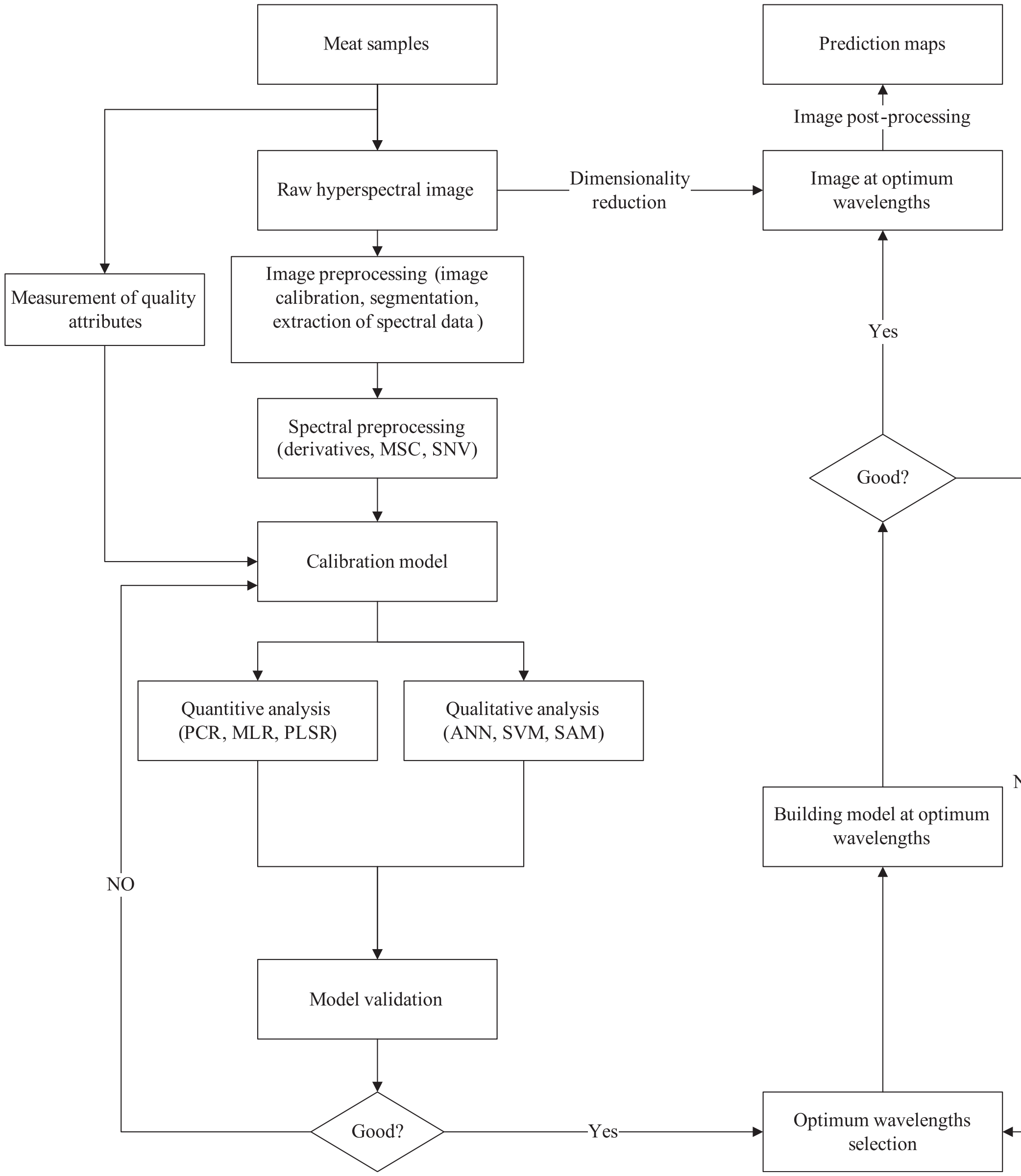

Fig. 4. A flowchart showing the routine of hyperspectral imaging processing.

researchers have explored PLS or PCA in conjunction with back propagation neural network (BPNN) (PCA-BNN) to develop models for predicting quality attributes of fruit, which gave satisfactory prediction results (Liu et al., 2010). Therefore, combination with multiple multivariate methods for modeling will be another feasible way for predicting quality attributes of red meats in future.

3. Recent advances in detecting quality attributes of red meats using hyperspectral imaging

In recent years, the hyperspectral imaging technique has been extensively implemented for meat quality evaluation and detection, especially for red meats, which mainly include pork, beef and lamb meats. Table 2 summarizes recent applications of hyperspectral imaging techniques in detecting quality attributes of red meats. Currently, applications of hyperspectral imaging in detecting quality attributes of red meats mainly contain prediction of microbiological spoilage, chemical components (protein, fat, moisture, etc.), color, tenderness, marbling level, drip loss, pH, and WHC. To a certain extent, the procedures of quality attributes prediction using hyperspectral imaging systems are somehow similar. Fig. 4 shows a common flowchart of detecting quality attributes of red meats using hyperspectral imaging systems. In the following sections, a detailed analysis of these applications will be given.

3.1. Measurements of chemical attributes

It is known that red meats are mainly composed of water, protein, fat, inosinic acid, amino acids, fatty acids and so on. Chemical constituents of red meats are intrinsic reasons that affect red meat quality. Through a series of reactions among different chemical constituents, flavor, color, as well as tenderness of red meats may change and thus result in bad appearance, which not only influence consumers' buying decision but also lead to economic loss for the meat industry. For example, moisture, which generally refers to the total water content of meat, is the major chemical constituent in red meats. The moisture content of red meats not only affects their quality but also their shelf-life, and any depletion of water will influence the economic profits of red meats as they are usually sold by weight. Moreover, the moisture content of red meats determines their juiciness, and variation of moisture content will surely affect the eating quality of red meats. Besides moisture, protein is also a main component in red meats. Red meats contain many different kinds of proteins, which are easily digested and absorbed by human body for essential good health. Furthermore, the protein in red meats often has a high biological quality and plays an important role in determining the quality of red meats by affecting their flavor and color (Goll, 1992; Young and West, 2001). In addition, fat and fatty acids are another two major components of red meats, which contribute to the flavor when they are cooked. Particularly, intramuscular fat, which is present with the lean protein fibres in the muscle, has a positive influence on eating satisfaction because little intramuscular fat possibly results in cooked products that lack flavor and juiciness (Fernandez et al., 1999). As most of the existing methods for detecting the major components of red meats are destructive, time-consuming and require long preparation times, it is emergent for the meat industry to seek out rapid and automatic methods to achieve nondestructive detection of these chemical constituents.

In the past few years, hyperspectral imaging systems as a smart and nondestructive method have been used for predicting the content of water, fat and protein in pork, beef, and lamb (ElMasry et al., 2013; Kamruzzaman et al., 2012b; Barbin et al., 2012b; Kobayashi et al., 2010), and these studies have shown encouraging results. For instance, Barbin et al. (2012b) developed a pushbroom hyperspectral imaging system in the near infrared range of 900–1700 nm for non-destructive determination of the protein, moisture and fat content in intact and minced pork. PLSR prediction models, established with a few selected feature-related wavelengths (eleven for protein, seven for moisture, and nine for fat), showed satisfactory results with R^2 of 0.92, 0.87, 0.95 of protein, moisture, and fat respectively.

In addition to pork, Kobayashi et al. (2010) used a laboratory hyperspectral imaging system in the near infrared range between 1000 and 2300 nm for assessing the fat and fatty acid content in intact raw beef cuts. By extracting the mean spectrum from the hyperspectral image, they developed PLSR models for prediction of fat and fatty acid content. Results showed that the extracted spectral characteristics of hyperspectral images could successfully predict total fat, total saturated fatty acid and total unsaturated fatty acid with a high correlation coefficient (R^2) of 0.90, 0.87 and 0.89 and standard error of prediction (SEP) of 4.81%, 1.69% and 3.41%, respectively. Another study about chemical constituent prediction of beef was tested by ElMasry et al. (2013). The established PLSR models also showed a reasonable accuracy for predicting water, fat and protein contents with R^2 of 0.89, 0.84 and 0.86, respectively.

Lamb meats are another important kind of red meats, but few studies about predicting quality attributes of lamb meats using hyperspectral imaging have been reported. Kamruzzaman et al. (2012b) were the first in using the hyperspectral imaging system (900–1700 nm) for prediction of the protein, fat, and moisture content in lamb meat. In their study, a total of 126 hyperspectral images of three different muscle samples (*Musculus semimembranosis*, *Musculus semitendinosus* and M. *longissimus dorsi*) were acquired. After a series of data processing, six wavelengths (960, 1057, 1131, 1211, 1308, and 1394 nm) were selected as the most relevant wavelengths in the spectrum for fat and water prediction, while another six wavelengths (1008, 1211, 1315, 1445, 1562 and 1649 nm) were selected for protein prediction. The PLSR models based on the selected wavelengths were established and showed good prediction abilities for these chemical constituents with determination coefficient R^2 of 0.84, 0.87 and 0.82 and SEP of 0.57%, 0.35% and 0.47% for water, fat and protein contents, respectively. As this was the first reported study in nondestructive detection of lamb meat using hyperspectral imaging, it should encourage future research for detecting other quality attributes of lamb meats. The above studies indicated that hyperspectral imaging has considerable potential for predicting chemical compositions of red meats.

3.2. Measurements of microbiological attributes

Spoilage in red meats is caused by the growth and enzymatic activity of microorganisms, which could result in the decomposition of nutrition matter and the formation of metabolites. Red meats with excessive bacteria cause harm to human health, thus it is critical to guarantee the safety of red meats supplied to the markets. However, the present traditional methods for bacterial spoilage detection, such as plate count method, enumeration methods based on microscopy, ATP bioluminescene, and the measurement of electrical phenomena, cannot achieve rapid, accurate and non-destructive detection of bacterially contaminated meat. Hyperspectral imaging can satisfy all these requirements, and its potential for predicting microbiological attributes of red meats has been intensively studied throughout many research endeavors (Wang and Zhang, 2010a; Tao et al., 2012; Peng et al., 2009; Peng and Wang, 2008). Among these studies, the majority of them used linear regression methods for modeling. For example, Wang and Zhang (2010a) used hyperspectral reflectance imaging for assessing the total plate count on chilled pork surface, and two prediction models were established using MLR and PLSR, giving encouraging results with R = 0.886 and 0.863 respectively. In addition to hyperspectral reflectance imaging mentioned above, which is commonly used, hyperspectral scattering technique could be also a potential method in detecting microbiological spoilage, because the changes in scattering profiles are able to represent the changes in microbiological spoilage. For instance, a hyperspectral scattering technique has been applied in detecting *Escherichia coli* contamination of pork (Tao et al., 2012). In this study (Tao et al., 2012), the scattering profiles were fitted by Lorentzian distribution to give three parameters a (asymptotic value), b (peak value) and c (full width at $b/2$). The results showed that MLR models based on parameters a and "$a\&b\&c$" gave high R of 0.877 and 0.841, respectively. Furthermore, hyperspectral scattering technique has also been used to detect TVC of beef (Peng et al., 2009), in which a MLR prediction model was developed based on relating individual Lorentzian parameters and their combinations at different wavelengths to $\log_{10}$(TVC) value. The best prediction were acquired with $R^2 = 0.96$ and SEP = 0.23 for $\log_{10}$(TVC). Although PLSR or MLR is promising, neither is able to solve nonlinear regression problems, thus some researchers used nonlinear modeling methods instead such as ANN, SAM, and SVM (Peng and Wang, 2008; Wang et al., 2011). For example, Peng and Wang (2008) have successfully developed a hyperspectral imaging system based on SVM for detecting TVC of bacteria in pork meat with R = 0.87, and the results were better than that of MLR methods. In order to improve the accuracy of prediction models, Wang et al. (2011) attempted to use the hyperspectral imaging system coupled with the least square support vector machines (LS-SVMs) for predicting the TVC of pork. Eight optimal wavelengths (477, 509, 540, 552, 560, 609, 720 and 772 nm) were selected to construct the TVC prediction in conjunction with the corresponding reflective spectrum data at these wavelength. The ultimate model with $R^2 = 0.9236$, RMSEV = 0.3279, indicated that the hyperspectral imaging system in conjunction with LS-SVMs could be more efficient to predict the TVC of pork.

3.3. Measurements of sensory attributes

Currently, detecting sensory attributes of red meats using hyperspectral imaging systems are mostly focused on prediction of color, marbling and tenderness. Sensory attributes are the main quality attributes that influence consumers' overall evaluation of red meats. On one hand, color and marbling highly affect consumers' buying decisions as consumers usually use the two attributes as indicators of freshness and wholesomeness. On the other hand, tenderness of red meats is an eating quality attribute, which cannot be evaluated directly by consumers. Therefore, prediction of these sensory attributes from fresh red meats is a major concern for the meat industry.

3.3.1. Color

Color is an important quality attribute, which can determine the grade or suitability of red meats coupled with other attributes. Beef meat and lamb meat in bright red and pork in pink are desirable, which will be attractive to consumers. Undesired surface color can make retailers cut their prices, resulting in revenue losses. Most commonly, color is measured by colorimeters in $L^*a^*b^*$ color space, where L^* represents the brightness, a^* the red–green color and b^* the blue–yellow color axis. However, the colorimeter cannot measure the color of the whole surface if samples are non-homogeneous, and with the measured area enlarging, unreliable results may come out because of intramuscular fat and connective content. With the rapid development of hyperspectral imaging systems, some authors try to explore their potential in color evaluation (Qiao et al., 2007a; Barbin et al., 2012c; ElMasry et al., 2012c; Wu et al., 2012b). Qiao et al. (2007a) developed a hyperspectral imaging system for prediction of color value L^* by extracting spatial and spectral information simultaneously. Based on simple correlation analysis, six wavelengths (434, 494, 561, 637, 669 and 703 nm) were selected as the optimum wavelengths. Then, two FNN-based prediction models were established using two intensity indices (R and R') of the band images as inputs respectively. The results showed that model 2 (R' as input) performed better than model 1 (R as inputs), with higher R^2 of 0.86. Besides predicting the value of L^* only, Wu et al. (2012b) applied hyperspectral scattering techniques to predict all three color parameters (L^*, a^*, b^*) in fresh beef meat. In this study, the scattering profiles were firstly derived from hyperspectral images and then fitted to the Lorentzian distribution (LD) function for extracting necessary parameters for L^*, a^*, and b^* values prediction. Finally, a MLR model was established using the LD parameters in conjunction with optimal wavelengths, and the results demonstrated that hyperspectral scattering technique was also a powerful approach to predict color parameters (L^*, a^* and b^*) in beef, with R of 0.96, 0.96 and 0.97, respectively.

3.3.2. Marbling

Marbling, which is also called intramuscular fat, refers to the white flecks of fat present within the lean muscle in the meat. Red meats with uniformly and finely distributed marbling are always considered as superior products, and consumers pay higher prices for them. Some previous studies have demonstrated that a close relationship between marbling level and palatability of red meats exist (Brooks et al., 2000; Kim and Lee, 2003), as marbling level can highly influence meat tenderness and juiciness (Fortin et al., 2005). In addition, intramuscular fat can give meat a distinctive aroma when it is cooked (Fernandez et al., 1999). Therefore, marbling is an important quality attributes of red meats, but most meat processers evaluate the marbling level by comparing the intramuscular fat within the M. *longissimus dorsi* against marbling reference standards of each meat species. Although this method is carried out by graders with good experience, it is still a subjective judgment and the consistency among these graders cannot be guaranteed. Therefore, there is a need for an objective method for marbling assessment for the meat industry. In recent years, some researchers have applied hyperspectral imaging systems in marbling evaluation and with good results obtained (Qiao et al., 2007b; Li et al., 2011a). For example, Qiao et al. (2007b) developed a hyperspectral imaging system for predicting the marbling level of pork meat. In their study, spatial features of pork samples were extracted for marbling assessment. In addition, marbling reference standards were scanned, and indices of the marbling scores (from 1.0 to 10.0) were determined by co-occurrence matrix. Finally, angular second moment (ASM) was applied to predict marbling scores, which gave a successful result except for the standard score 10.0. A total of 40 pork samples were detected and their marbling scores mostly ranged from 3.0 to 5.0. Besides pork meat, marbling level of beef meat has also been assessed using a hyperspectral scanning imaging system in the spectral region of 400–1100 nm (Li et al., 2011a). In this study (Li et al., 2011a), some characteristic bands were selected according to the maximal ratio of gray value of fat and lean in each band. Consequently, the images at 530 nm were utilized to differentiate marbling level of beef samples. With three extracted characteristic parameters, a MLR prediction model was finally established, which gave an encouraging result with $R^2 = 0.92$ and $SE_{CV} = 0.45$.

3.3.3. Tenderness

Tenderness, an expression of meat texture, is regarded as one of the most important sensory quality attributes as it highly influences consumer satisfaction (Rødbotten et al., 2000). As mentioned above, the most common method to evaluate tenderness of red meats is to use a WBSF or SSF, but both of them are not suitable for rapid prediction and on-line applications. Recently, interests in exploiting instruments that can achieve fast and non-destructive assessment of meat tenderness are growing. In this aspect, hyperspectral imaging systems have great potential, which has been demonstrated by many studies (Naganathan et al., 2008; Kamruzzaman et al., 2013; Tao et al., 2012; Cluff et al., 2008; ElMasry et al., 2012c). For example, Naganathan et al. (2008) used a visible/near-infrared hyperspectral imaging system to assess tenderness of 14-day aged beef. Hyperspectral images of beef samples were acquired at 14-day post-mortem. Then, spatial and spectral features of the hyperspectral images were extracted using PCA and a co-occurrence matrix. On the basis of the extracted features, a discriminant model was established. Furthermore, with a leave-one-out cross-validation procedure, the model predicted three tenderness categories (tender, intermediate, and tough) with an accuracy of 96.4%. Besides, some authors used hyperspectral scattering techniques to predict tenderness of red meats, because the changes in scattering profiles can represent the changes in tenderness. For instance, Tao et al. (2012) applied the hyperspectral scattering technique to predict tenderness of pork meat, and the final prediction model established with MLR methods gave high R^2, ranging from 0.831 to 0.930. In addition, Cluff et al. (2008) developed a hyperspectral scattering imaging system to predict tenderness of beef meat. In their study (Cluff et al., 2008), a total of sixty-one steaks were scanned. Then, the optical scattering profiles were derived from the hyperspectral images, and these profiles were used to extract useful parameters for predicting the WBSF values. The result demonstrated that hyperspectral scattering imaging technique was able to predict WBSF values with R of 0.67. On the other hand, there was only one study about tenderness prediction of lamb meat using a hyperspectral imaging system (Kamruzzaman et al., 2013), in which SPA as a new method for wavelength selection was used to select the most representative wavelengths (934, 964, 1017, 1081, 1144, 1215, 1265, 1341, 1455, 1615 and 1655 nm) for predicting WBSF values. The ultimate models established with PLSR methods gave good results in prediction ($R^2 = 0.84$) and categorization (89%) of lamb meat based on WBSF values.

3.4. Measurements of technological attributes

3.4.1. pH

pH is a chemical concept, which refers to the concentration of the hydrogen ion in aqueous solution, and has great influence on the storage and quality of red meats by affecting their water holding capacity and color. pH values of normal muscles are between 7.1 and 7.3, which changes a lot in postmortem. After slaughter, metabolism in muscle is still going on in order to keep the internal environment stable. During this process, the substrates glycogen, glucose, and glucose-6-phosphate are converted to lactate through anaerobic glycolysis. The accumulation of lactate coupled with protons released from adenosine triphoshpate hydrolysis leads to a pH decline in muscles (El Rammouz et al., 2004). The rate and extent of pH decline have a great impact on the shelf life of red meats and their eating quality. In detail, two main adverse cases related to pH in meat quality can be concluded: one is pale, soft and exudative (PSE) meat and the other one is dark, firm and dry (DFD) meat (Barbut et al., 2008; Honikel and Fischer, 1977). PSE meat results from a rapid pH decline in postmortem, and DFD meat is due to a high ultimate pH (Honikel and Fischer, 1977). Red meats in both cases are usually considered as inferior products as these meats not only have a bad taste but also less acceptable in color, and may have a shorter shelf-life. Traditionally, pH is measured by inserting a pH meter into the muscle directly after incision of the muscle, but nowadays, there is a potential to predict pH using hyperspectral imaging systems (Barbin et al., 2012c; Qiao et al., 2005; Wu et al., 2010; Kamruzzaman et al., 2012c). For example, Qiao et al. (2005) developed a hyperspectral imaging system, which could extract both spectral and spatial characteristics of hyperspectral images, for determination of pH in pork meat. In their study (Qiao et al., 2005), six wavelengths (430, 448, 470, 890, 980 and 999 nm) were selected as feature wavelengths for predicting pH values. With these feature wavelengths, a feed-forward neural network model was finally established, which gave R^2 of 0.67. Another example to predict pH of pork meat using hyperspectral imaging was carried out by Barbin et al. (2012c), in which, several spectral preprocessing methods including SNV and MSC were first used to eliminate the influence of spectral variations. After extracting useful spectral information, a prediction model was then built up with a PLSR method. The ultimate results showed that pH could be well predicted using hyperspectral imaging systems with R^2 of 0.87. In addition, Wu et al. (2010) exploited the potential of hyperspectral scattering systems for pH prediction of beef meat, with the final MLR model showing good performance for pH prediction with $R_{CV} = 0.86$, $SE_{CV} = 0.07$. On the other hand, Kamruzzaman et al. (2012c) developed a NIR hyperspectral imaging system in conjunction with multivariate analysis for pH prediction of lamb meat. In this study (Kamruzzaman et al., 2012c), a prediction model was established with a PLSR method, and gave results with an R^2_{CV} of 0.65, RMSEC of 0.075, and RMSECV of 0.085. Besides RMSEC and RMSECV, the ability of the prediction model was also evaluated based on the RPD (ratio of prediction to deviation), which was defined as the ratio of standard deviation (SD) of the reference values over the RMSECV (RPD = SD/RMSECV). Generally, an RPD value greater than 2 indicates reasonable good prediction, and above 3 means excellent prediction accuracy and is considered adequate for analytical purposes (Nicolai et al., 2007). In this study, the RPD value was 1.76, meaning that the model was not so robust. Therefore, more research efforts should be intensified to improve the prediction accuracy of pH using hyperspectral imaging in future.

3.4.2. WHC

Red meats contain approximately 75% water (De Smet, 2012), and in the process of slaughter, storage and processing, it is easy to lose moisture in muscles. It is reported that moisture loss of fresh meat is generally between 1% and 3%, while for PSE meat the loss can even reach 10% (Huff-Lonergan, 2002). The ability of red meats to retain all or part of their own water is known as WHC, which is a major quality attribute as it determines the juiciness of red meats (Wierbicki and Deatherage, 1958). For the meat processing industry, predicting the WHC of red meats is essential because WHC is an indication for weight loss in raw, cooked, as well as processed meats. In the last decades, many studies have been carried out to investigate pre- and post-mortem factors influencing WHC of red meats. As we know from these studies, these factors can be generally sorted into intrinsic (genotype) and extrinsic (fasting, stunning, pre-rigor temperature, etc.) factors. There are a variety of techniques for the determination of WHC such as drip loss, cooking loss, filter paper wetness, and processing loss (Petracci et al., 2011). However, most of these traditional methods are time consuming and destructive and cannot be applied in real-time applications. Therefore, new non-contact and nondestructive methods have been introduced to solve these difficulties, and among them, hyperspectral imaging is particularly promising. For instance, ElMasry et al. (2011) developed a near-infrared hyperspectral imaging system for nondestructive prediction of WHC in fresh beef. PCA were used to extract feature wavelengths, leading to the selection of six important wavelengths (940, 997, 1144, 1214, 1342, and 1443 nm) for establishing a prediction model with the PLSR method. The model gave a reasonable accuracy to predict drip loss with R^2 of 0.87 and SECV of 0.28%.

4. Future prospects

Hyperspectral imaging is a powerful technique for predicting essential attributes of red meats such as pH, color, tenderness, WHC, marbling and so on. It fuses the merits of traditional imaging and spectroscopy techniques, and can simultaneously achieve nondestructive detection and visualization of different quality attributes. However, there are still some barriers to overcome. First of all, the issue of high dimensionality of hyperspectral data is a challenging task, which could limit their implementations for on-line systems. Therefore, developing cost-effective and efficient algorithms are needed in order to solve the difficulties of hyperspectral data processing and to satisfy the requirements of industrial applications. Secondly, some quality attributes of red meats, such as tenderness, hardness and springiness, are related to linear factors such as the content of myofibrillar proteins and non-linear factors such as muscle structure (connective tissue). In this case, not only linear methods but also non-linear methods can be used for modeling. However, as can be seen from Table 2, most of the studies have used linear methods such as PLSR and MLR to establish prediction models. Although these linear methods are promising, additional studies are necessary to apply non-linear methods for modeling. Thirdly, as a hyperspectral imaging system has a mass of data and high cost, a multispectral imaging system with a limited number of wavebands can meet the requirements of real-time acquisition and processing. Therefore, seeking the most sensitive wavebands to predict the essential quality attributes of red meats and building up a multispectral imaging system will be practical in industrial application. Fourthly, the costs of hardware of hyperspectral imaging systems will have to keep going down with the development of technology and improvement in sensors, illumination units, as well as computers. On the other hand, software, such as MATLAB and ENVI, plays an important role in hyperspectral data processing, but their selling prices are high. Therefore, it is necessary to seek approaches that can reduce the prices of software. For example, software companies should attempt to develop cheaper software, which contain similar functions like MATLAB or ENVI. Finally, current studies using hyperspectral imaging systems are mostly focused on extracting and using the spectral information without combining spatial information (Barbin et al., 2012b; Qiao et al., 2005). Some authors have already realized the importance of spatial information, and have attempted to extract useful spatial information from hyperspectral images with some analysis techniques such as the gray level co-occurrence matrix (Kamruzzaman et al., 2013; Naganathan et al., 2008). Therefore, the development of techniques that are able to extract spatial information has great potential in predicting quality attributes of red meats.

5. Conclusions

This review paper has mainly introduced recent developments of hyperspectral imaging systems in the aspects of hardware and software as well as recent advances in detecting quality attributes of red meats using hyperspectral imaging. With the rapid development of science and technology, the cost of hardware can significantly be reduced and the speed for update becomes fast. On the other hand, software for data processing has also made progress, which obviously focuses on more novel algorithms developed for feature wavelength selection, spectral preprocessing, and model establishment. Besides introducing the development of hyperspectral imaging systems, applications of hyperspectral imaging in detecting quality attributes of red meats have also been presented in the paper, mainly including prediction of the content of chemical compositions, color, pH, marbling level, tenderness, WHC and so on. These studies have fully demonstrated that hyperspectral imaging as a rapid and non-invasive technique would be promising for other quality attributes detection in future. However, there are still some barriers to be solved, such as dimensionality reduction problems, and new algorithms exploitation for establishing prediction models in a commercial and real-life environment. The future trend of the hyperspectral imaging technique is to exploit advanced devices, develop powerful and easy-to-use software and apply non-linear methods or combine with multiple multivariate methods for modeling.

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