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Spectral Detection Techniques for Non-Destructively Monitoring the Quality, Safety, and Classification of Fresh Red Meat

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Abstract

Red meat is an important source of nutrients and plays a significant role in human diet. With the development of people's living standard and relative change of dietary structure in recent years, people propose more requirements for meat. Quality, safety, and classification are three crucial themes related with meat and they are important issues for consumers, retailers, as well as the whole meat industry. However, most of the traditional analytical methods for meat evaluation are time-consuming, laborious, tedious, and destructive, which make them inappropriate for fast analysis and early detection, especially under fast-paced production and processing environment. In contrast to conventional approaches, spectral techniques including near infrared spectroscopy (NIRS), hyperspectral imaging (HSI), and Raman spectroscopy (RS) have emerged and considered as promising tools for meat assessment. The innovative optical sensing techniques can facilitate simple, fast, accurate, and simultaneous measurements of multiple meat attributes. Recently, these techniques have achieved rapid development and attracted more attention of the public. Hence, the goal of this article is to give an overview of the current progress of the spectral techniques for evaluation of fresh red meat (pork, beef, and lamb). The spectral techniques are described in terms of their basic working principle, fundamental configurations, analysis process, as well as applications on meat inspection. In addition, the problems to be tackled and future potential trends of these spectral methods are also discussed in this paper.

Keywords Red meat · Vis/NIR · HSI · RS · Quality · Safety · Classification

Introduction

Meat, particularly red meat, is of utmost importance in human's diet as it includes high content of easily digestible protein, essential fatty acids (FAs), and other micro-nutrients that are beneficial to health (Wojnowski et al. 2017). According to Food and Agriculture Organization (FAO) of the United Nations, the total amount of global meat production is about 3.207 million t in 2016, which indicates the meat industry's immense potential for development. In the last few decades, meat consumption patterns have changed and consumers are increasingly demanding meat that is of higher intrinsic quality, guaranteed safety, and having increased functional and nutritional properties (Papadopoulou et al. 2011). This has resulted in research interests in techniques that determine the quality, safety, and classification, which are three crucial aspects related with meat.

In many studies, safety is regarded as part of quality. However, we consider these aspects independently. Quality is analyzed in the context of how humans perceive meat, while safety is evaluated with respect to threats to health (Alander et al. 2013). Quality encompasses eating quality attributes and chemical attributes (Miller 2017). Eating quality attributes include color, marbling, flavor, tenderness, juiciness, and water holding capacity (WHC), which determine the sensory or masticatory impression on meat. Chemical attributes, such as water, protein, intramuscular fat (IMF), and FA, describe the main compositions of meat and are closely related to its nutritional value. Of all the chemical attributes, FA profiles are increasingly drawing attention owing to the effect of the amount and type of FA on eating quality, such as tenderness and flavor (Gonzalez-Martin et al. 2005), as well as its close relationship with cardiovascular diseases. Meat safety is a top priority as it is associated with human health. Safety could be challenged in various ways (Saucier 2016), of which micro-

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organism-associated issues are the most serious threat in terms of both foodborne illness and product recalls (Lianou et al. 2017). This is because meat provides a suitable growing environment for spoilage and foodborne pathogens. Microbial contamination may occur in the process of production, storage, distribution, retailing, and consumption. Furthermore, chemical contaminants and residues, such as veterinary drug and pesticide residues, may also impact meat safety. The contaminations may be caused by man-made, natural, or mineral toxins, which pose great health risks to humans (Dasenaki and Thomaidis 2017). Another aspect that caught our attention was the classification of meat, which includes the authenticity issues and discrimination based on the quality attributes. According to Ballin (2010), authentication can be divided into four major categories, namely identification of meat origin, meat substitution, meat processing treatment, and non-meat ingredient additions. The discrimination involves the differentiation of red firm non-exudative (RFN) meat, pale soft exudative (PSE) meat, and dark firm dry (DFD) meat, the distinction between tender and tough meat, and so on.

Traditional analytical methods, such as sensory evaluation, chemical analysis, and micro-biological analysis, have been used for decades. They are considered effective, reliable, and capable of providing consistent results (Peng and Dhakal 2015). However, these methods require well trained assessors or are generally time-consuming, tedious, labor-intensive, and destructive (Alander et al. 2013). To satisfy demands of producers, manufacturers, distributors, retailers, and especially consumers, the meat industry requires innovative technologies to realize objective and reliable meat evaluation at all stages of the commodity chain. Spectroscopic techniques have emerged as possible methods, and they have exhibited many advantages over traditional methods such as easy handling, high speed, cost efficiency, and the capacity of automated measurements for repetitious tasks. Besides, they are also potential tools for on-line or in-situ detection owing to their capacity for high throughput analysis, which is an attractive factor from the industrial point of view. Among, near infrared spectroscopy (NIRS), hyperspectral imaging (HSI), and Raman spectroscopy (RS) are three commonly used techniques for meat inspection (Chen et al. 2013).

A number of reviews have been published on their applications for food evaluation as summarized in Table 1, which involves the quality and safety assessment of meat, fish, beverage, and so on. The papers demonstrated that such spectral methods have been implemented as alternatives to conventional methods. Considering the importance of red meat, a systematic introduction to the recent applications of spectroscopic methods in red meat is urgently needed. Besides, the published reviews cover only one aspect of the applications, a comprehensive review on the applications of three crucial aspects of quality, safety, and classification is lacking.

Therefore, the specific goal of this article is to present an overview of the current research progress and applications of three spectroscopic techniques (NIRS, HSI, and RS) for monitoring quality, safety, and classification in fresh red meat (pork, beef, and lamb). The specific objectives of this review

Table 1 Summary of the applications of spectral technology in food evaluation

Technology	Product	Target attributes	Reference
NIRS	Food	Quality	Davies and Grant (1987)
NIRS	Food and agriculture	Component concentration	Martin (1992)
NIRS	Meat	Chemical composition and quality	Prevolnik et al. (2004)
NIRS	Food	Quality	Cen and He (2007)
NIRS	Food and beverages	Quality	Woodcock et al. (2008)
NIRS	Meat and meat products	Quality	Prieto et al. (2009a)
NIRS	Muscle food	Quality and safety	Weeranantanaphan et al. (2011)
NIRS	Intact muscle	Quality	Reis and Rosenvold (2014b)
NIRS, HSI, RS, and infrared thermal imaging	Meat	Quality	Troy et al. (2016)
HSI	Agro-product	Quality and safety	Peng and Zhang (2013)
HSI	Food	Quality and safety	Wu and Sun (2013)
HSI	Red meats	Quality	Xiong et al. (2014b)
HSI	Pork, beef, and lamb	Quality attributes	Xiong et al. (2014a)
HSI	Raw and processed agricultural and food products	Microbial contaminants	He and Sun (2015)
HSI	Meat, poultry, and fish	Contamination, adulteration, and authenticity	Kamruzzaman et al. (2015)
HSI	Muscle	Quality attributes, muscle classification	Cheng et al. (2017)
RS	Fish and meat	Quality assessment	Herrero (2008)
RS	Agricultural products and food	Quality assessment	Yang and Ying (2011)

are as follows: (1) to introduce their basic working principle, fundamental configurations, and analysis process and focus on the recent advances and applications in meat assessment especially after 2010; (2) to discuss the problems and challenges that must be addressed for further application; and (3) to analyze the development and application tendency of these three spectral techniques.

Spectral Methods and Techniques

Near Infrared Spectroscopy

NIRS is based on the absorption of electromagnetic radiation in the range of 780~2526 nm. It is related with molecular vibrations, especially the overtones and combination bands of vibrational modes in the form of C-X, where X is carbon, nitrogen, or oxygen (Cabassi et al. 2015; Kumar and Chandrakant Karne 2017; Lohumi et al. 2015), and the commonly observed bonds in the NIR region are summarized in Table 2 (Stuart 2005). A general NIRS system mainly consists of light source, optical detector, computer, and beam splitter system, as shown in Fig. 1 (Cen and He 2007). Generally, NIR measurements can be performed in reflectance, interactance, or transmittance mode (Qin and Lu 2008). Meat is usually recorded in the reflectance mode, in which case, the illuminant and detector are placed on the same side of sample and the reflected light is captured by the detector after repeated reflection, refraction, absorption, and diffraction (Gou et al. 2013). Of all the optical technologies, NIRS is the most flexible as it can separate the sampling position from the spectrometer by means of a light-fiber probe, and this is the reason why NIRS is suitable for on-line process monitoring (Ozaki 2012).

After acquisition of NIR spectra, chemometric tools are usually required to relate them and reference values. Pretreatment methods, such as smoothing, derivative, and multiplicative scatter correction (MSC) are commonly used methods to eliminate the adverse effects. Mathematical and statistical tools including partial least square (PLS), multiple linear regression (MLR), principal component regression (PCR), and support vector machine (SVM) are required to build models (Arvanitoyannis and van Houwelingen-Koukaliaroglou 2003). In addition, sample grouping methods, elimination of abnormal samples, and characteristic wavelength selection approaches also play a crucial role in building a robust model. A more detailed introduction about the multivariate analysis approaches was given by Porep et al. (2015).

The application of NIRS for meat detection can be traced back to 30 years ago, when silicon detector was developed and allowed acquisition of spectra in the range of 700~1100 nm. This improvement enabled the analysis of meat, which is a kind of high-moisture sample (Alander et al. 2013). Subsequently, along with the evolution of optical instrument and improvement of chemometrics methods, NIRS technology has undergone rapid development. Numerous researches which aimed at exploring the feasibility of NIRS in meat evaluation have been conducted, and satisfactory results were obtained (Brøndum et al. 2000; Hoving-Bolink et al. 2005; Prieto et al. 2006; Prieto et al. 2008). However, there are still some problems to be tackled for its further application in meat industry. Hence, in recent few years, most work focused on improving the prediction accuracy and establishing robust and practical models. Besides, another noteworthy improvement is the development of portable or hand held spectrometer, which has facilitated on-line or in-situ applications of NIRS. It is worth mentioning that as the visible (Vis) region is commonly involved in NIR instrument, the following applications also cover the visible region.

Quality Analysis Using NIRS

The potential of NIRS for prediction of quality traits has been examined extensively, and in recent years, many researchers are devoting themselves to improving the model robustness. Zamora-Rojas et al. (2011) conducted a study on the development, validation, and updating of NIRS models for routine analysis of IMF, water, and protein in pork. The Global (GH) and Neighborhood (NH) Mahalanobis were proposed and used to select samples for recalibration, and good spectral matching for muscles that were not included in the calibration was observed. Further, the influence of muscle breeds and types on the calibration models was reported by Mourot et al. (2015). In their work, FA compositions of beef from four breeds and three muscles were predicted with determination coefficient of cross-validation (R_{cv}^2) > 0.86. Their study indicated that including several types of muscles in a global calibration model was necessary for industrial application. In another study conducted by Zhang et al. (2012b), pig carcasses of different breeds were collected from three markets for water prediction. The comparison of modeling results showed that SVM performed better than PLS with correlation coefficient in the prediction set (R_p) of 0.87. The precision was lower than that of Cheng et al. (2012), who used Fourier transform near-infrared spectroscopy (FT-NIRS) to detect water in minced pork. Muscles from three different parts were collected and least square support vector machine (LS-SVM) model was built, which gave an R_p of 0.90. The comparison of their studies showed that the sample presentation had an effect on the model results. This conclusion was verified by Guy et al. (2011), who compared the results for FA compositions in ground and intact lamb samples. Their study indicated that the PLS models with ground samples performed better than intact samples with higher R_{cv}^2. The reasons may be that homogenization would severely alter the muscles structure, and the fiber arrangement is also destroyed and randomized. Then the scattering effects caused by the fibers will be averaged,

Table 2 Common near-infrared bands of organic compounds (Stuart 2005)

Wavelength (nm)	Assignment
2200~2450	Combination C-H stretching
2000~2200	Combination N-H stretching, combination O-H stretching
1650~1800	First overtone C-H stretching
1400~1500	First overtone N-H stretching, first overtone O-H stretching
1300~1420	Combination C-H stretching
1100~1225	Second overtone C-H stretching
950~1100	Second overtone N-H stretching, second overtone O-H stretching
850~950	Third overtone C-H stretching
775~850	Third overtone N-H stretching

which result in better predictive performance for chemical attributes (Barlocco et al. 2006). However, the destruction of natural structure and randomized arrangement of muscle may also result in the loss of muscle information, leading to poor prediction performance for physical attributes, for example, Warner-Bratzler shear force (WBSF) (Prieto et al. 2009b). Besides, although the milling treatment may help guarantee accurate prediction results, it is a time-consuming phase and cannot satisfy the requirement of meat industry for non-destructive and real-time analysis.

Hence, more attention was paid to improving models based on intact meat. Tang et al. (2013) compared different pretreatment and modeling methods to determine water content in beef. The PLS model based on spectra after MSC yielded the best result with R_{p} of 0.92 and standard error in the prediction set (SEP) of 0.0047. More recently, in another study on predicting beef water using NIRS, the authors tried cluster analysis of particle swarm optimization (PSO) algorithm to reduce computation complexity and optimal PLS model was established with R_{p} of 0.9191 (Tang et al. 2014). Their work showed that selection of appropriate pretreatment methods and spectral range is conducive to improve spectral interpretation capability and eliminate unwanted information. In addition to these studies on algorithm, improvements in hardware also contribute to the optimization of models. To increase the sampling area and improve spectral representativeness, Zheng et al. (2016) used a ring light guide instead of a point light illumination to establish a NIRS system in the range of 400~2450 nm. The comparison of spectra and variation coefficient indicated that the former performed better than the latter with more stable and comprehensive spectral information. Dixit et al. (2016) reported another study to evaluate the capacity of collimated light and multipoint NIR spectroscopy system in estimating IMF, protein, and water of beef. The spectrophotometer had four channels, which enabled the simultaneous measurements of four positions and overcame the drawback of lacking representativeness for single-point measurement. They obtained good results with determination coefficient in the prediction set (R_{p}^2) from 0.90 to 0.97 for IMF, water, and protein at three modes (static, slow rotational motion, and fast rotational motion).

Other factors that influence the model results were also discussed. Prevolnik et al. (2010) explored the effect of reference values analytical methods on the prediction capacity. The authors used EZ drip loss, cooking loss, centrifuge force, and tray drip loss for determination of WHC in pork. The best results were achieved based on EZ drip loss and tray drip loss, which gave R_{cv}^2 of 0.62 and 0.49, respectively. However, the model precision was low, which restricted its implementation at industrial level. The results also demonstrated that the reliable and repeatable reference values were critical for a robust

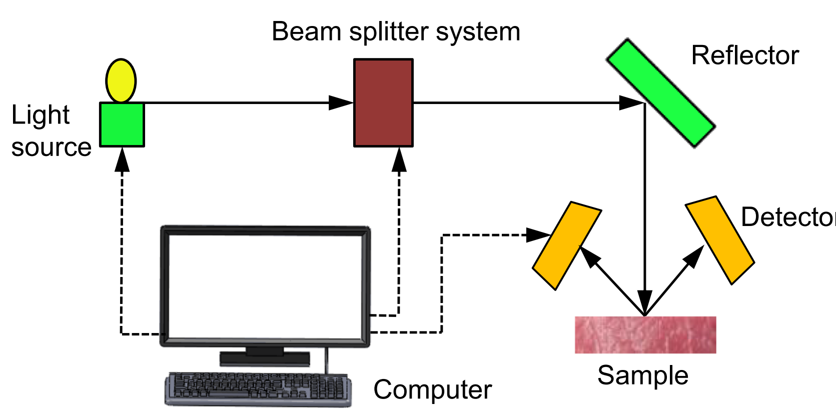

Fig. 1 Basic composition of a NIRS acquisition system

model. In another study conducted by Liu et al. (2014b), they discussed the influence of distance between fiber optical and sample on prediction accuracy. Vis/NIR spectra at distances from 4 to 18 mm were collected, and then PLS models for tenderness were established and compared. The spectra at distance of 13 mm yielded the best result, and then other spectra were calibrated to those at 13 mm. After calibration, the R_p and SEP increased to the range of 0.83~0.90 and 4.80~5.75 N. The results implied that setting the experimental parameters at the optimum state is the prerequisite for obtaining good results.

Another noteworthy progress was the miniaturization of instruments, which has prompted the on-line and in-situ inspection. By means of a conveyor, Liao et al. (2010) developed an on-line system for prediction of IMF, protein, water, pH, and shear force (SF) value. The R_p^2 for all traits were above 0.757 except for SF value. Later, the authors improved the model for pH by selecting characteristic variables with R_p of 0.89 (Liao et al. 2012). More recently, Zhang et al. (2013) designed an on-line real-time detection system which consisted of spectrometers, multiplexer, fiber optical, sensor, and conveyor to assess water in pork quality, and an R_p of 0.903 was achieved. In addition, Pullanagari et al. (2015) implemented NIRS under commercial abattoir condition for quantitative prediction of FA compositions in lamb. Based on the PLS models, individual fatty acids (IFA), saturated fatty acid (SFA), monounsaturated fatty acid (MUFA), and polyunsaturated fatty acid (PUFA) were predicted with R_{cv}^2 of 0.35~0.74. Although the results need further improvement, it was still considered as a potential screening tool for online determination of chemical compositions.

Apart from on-line detection system, further efforts were also made on developing portable device. Zamora-Rojas et al. (2013) compared a handheld micro-electro-mechanical system (MEMS) spectrometer with a high-resolution NIRS monochromator for prediction of main FAs in Iberian pig. The reasonable results indicated that the handheld spectrometer with low cost, high speed, and simple sample presentation would pave a new way for on-line application. Based on a portable spectrometer, Lin et al. (2014) and Sun et al. (2015) designed a portable detection device which was capable of non-destructively detecting multiple quality attributes. The device included ARM (advanced RISC (reduced instruction set computer) machines) processing unit, light source and detection unit, spectral data acquisition unit, LCD (liquid crystal display) touch screen display unit, and the cooling unit. Their work achieved the R_p of 0.88, 0.90, 0.97, 0.97, and SEP of 0.19, 1.77, 1.17, and 0.63 for pH, L^*, a^*, and b^*, which therefore indicated the great potential of the portable device for real-time detection directly at the selling points for quality control.

Safety Analysis Using NIRS

Spoilage is a significant standard to measure whether the meat meets with edible level and could synthetically reflect the security of meat. It is caused by microbial activity and will pose a great threat to human health. An important attribute for spoilage status determination is total viable counts (TVC), which is the collective name of psychrophilic micro-organisms reproduced in meat. However, the studies on using NIRS to predict microbial and chemical contamination in red meats are scant. Gu et al. (2013) exploited its capability in inspecting the TVC of pork stored at room and low temperature and an R_p of 0.92 was obtained. Long et al. (2014) applied NIRS over the spectral range of 460~940 nm to identify the spoiled pork from fresh pork. In this work, the authors tried different feature wavelength selection methods and discrimination algorithms for model establishment. The Fisher variance discrimination model based on 16 characteristic wavelengths performed the best with accuracy of 96.88 and 90.91% in the calibration and prediction set, respectively. The rare applications on the determination of microbial content and chemical pollutant concentration may be attributed to two reasons. On one hand, micro-organisms and chemical residues are unevenly distributed in meat, while the NIRS is based on point measurement. Hence, it is difficult to cover the comprehensive information of intact meat. On the other hand, the capacity of NIRS for predicting micro-organisms lacks of explanation, which has aroused many scholars' suspicion.

Total volatile basic nitrogen (TVB-N) is another crucial attribute to determine meat freshness, which is related with shelf life. As storage days pass by, alkaline nitrogen such as ammonia and amine was produced and combined with acidic substances within the organization to form TVB-N (Li et al. 2015). Meat is deemed to be semi-fresh or putrid when the TVB-N content is beyond 15 mg/100 g according to Chinese standard GB 2707-2016 (Li et al. 2017). In an early paper on this topic, Cai et al. (2011a) investigated the potential of FT-NIR for TVB-N content determination. The authors compared synergy interval PLS (siPLS) and classical PLS, and the results showed that si-PLS had incomparable superiority to PLS for the removal of unwanted information and retention of relevant variables. However, the model was not satisfactory with R_p less than 0.8. Recently, another study on prediction of TVB-N using feature wavelengths was reported Ma et al. (2013). In this work, uninformative variable elimination (UVE) and successive projections algorithm (SPA) were combined to select characteristic variables. Eight out of 1571 variables were then chosen, and high correlation with $R_p = 0.925$ was obtained using the LS-SVM method, which further highlighted the importance of the exclusion of irrelevant variables. In addition, as freshness is associated with storage time, there has been a substantial effort in using NIRS to predict storage time. For example, Wu et al. (2012b) conducted a study on using the NIRS in the range of 1000~2500 nm to discriminate the storage time, and good agreement with an average classification rate of 95% was observed.

Similar with the study of quality attributes, rapid, non-destructive, and real-time detection device for safety attributes has merged. Using the dual-band spectra over the range of 400~2500 nm, Wang et al. (2016) designed a detection device, which was equipped with hardware unit and software control program. The device could collect, real-time process, calculate, display, and preserve spectral information at the same time. The model for TVB-N was built with R_p of 0.9363, which indicated the great potential for further application.

Meat Classification Using NIRS

Authenticity is an important issue which has a negative impact on economy, and it may also derive problems with regard to religious laws or personal behaviors (Fontanesi 2017). NIRS has been successfully employed for discriminant analysis in early studies, such as identification of beef, pork, chicken and lamb meat (Cozzolino and Murray 2004), and discrimination among different types of ground beef (Prieto et al. 2008).

Recently, Cai et al. (2011b) carried out a study to differentiate beef with different regions and feeding periods. The NIR spectra showed significant difference, which paved the way for its application in geographical origin assignment and traceability. Mamani-Linares et al. (2012) investigated the potential of NIR reflectance spectroscopy for recognizing cattle with llama and horse meat. Meanwhile, the authors also used transflectance spectroscopy to identify meat juice with different species. PLS model based on the "dummy" variables gave good discriminating models with accuracy of 94.94 and 96.55% for meat and meat juice, respectively. More recently, Alamprese et al. (2013) compared the capacity of UV-Vis, NIR, and mid-infrared (MIR) spectroscopy in detecting minced beef adulteration with turkey meat. The results showed that the fused UV-Vis-NIR-MIR data matrix yielded the most satisfactory result than any single instrument. However, the cost-benefit ratio needs to be taken into consideration for further application. Apart from researches on fresh meat, studies were also conducted on processed meat. Morsy and Sun (2013) evaluated the potential of NIRS for detecting and quantifying adulterants (pork, fat trimming, and offal) in fresh and frozen-thawed minced beef. Satisfactory results with accuracy of 100% were obtained for discrimination of two types of meat. For the quantification of adulterants, good agreements with R_p^2 of 0.96, 0.94, and 0.95 were obtained for fresh meat, 0.93, 0.82, and 0.95 for frozen-thawed meat. A similar study was conducted by Alamprese et al. (2016) to identify minced beef adulteration with turkey meat using FT-NIR spectroscopy and multivariate analysis. Samples were presented as raw, frozen-thawed, and cooked, and then PLS models were built with R_p^2 higher than 0.884 and SEP lower than 10.8%. The results demonstrated that although the technological treatments may mask some possible interspecies adulteration, it is still considered feasible to use NIRS for meat identification in processed meat.

To discriminate meat based on their quality attributes using NIRS was also studied. Liu et al. (2014a) combined NIRS with PLS projection to discriminate RFN meat from PSE and DFD meat. Thirteen feature wavelengths were selected and employed for classification, and accuracy rates of 84.62, 94.11, and 84.62% were obtained. Reis and Rosenvold (2014a) reported another study for early on-line classification of carcasses in a commercial hot boning abattoir under routine conditions. In this work, the ultimate pH_u (48 h post-mortem) with a threshold of 5.8 was used to segregate carcasses as normal or high. Two separate models for bulls and non-bulls (steers, heifers, and cows) were built, both of which gave good results with classification accuracy of at least 90% for high pH_u carcasses. More recently, using the spectra from 400 to 1495 nm, Balage et al. (2015) conducted a study to categorize samples into tender or tough and juicy or dry. Accuracy of 72 and 73% was achieved for the classification of tenderness and juiciness class. Although their work demonstrated the great potential of NIRS, supplementary research is required to improve the prediction precision. In addition, portable instrument was also employed for discrimination of meat. Prieto et al. (2015) used a portable LabSpec®4 spectrometer to segregate pork samples according to pig breeds. Meanwhile, the authors also used it to discriminate moisture enhanced sample from non-moisture enhanced meat. Satisfactory results with accuracy of 97 and 99% for samples aged 2 days and 94 and 95% for samples aged for 14 days were obtained. However, the distinction of pork samples with different diets or from different carcass chilling processes needs further investigation.

Other applications of NIRS for detection of meat were summarized in Table 3.

Hyperspectral Imaging Technology

HSI technology has been proved to be a powerful analytical tool as it integrates both spectroscopic and imaging techniques in one system to provide spectral and spatial information of tested samples. A hyperspectral image contains much information in a three-dimensional (3D) form called "hypercube" (Kamruzzaman et al. 2012a; Kamruzzaman et al. 2015), among which two dimensions are coordinate information of spatial pixel, which are expressed in x and y, and the third dimension is wavelength information, which is represented with λ. As a combination and extension of traditional spectroscopy and digital imaging, it provides a more detailed description of internal and external attributes (Ravn and Bro 2008). Another strategic advantage of HSI technique is its capacity to generate chemical maps to show distributions of

Table 3 The applications of NIRS in meat industry since 2010

Sample	Sample form	Wavelength range (nm)	Pre-treatment method	Elimination of the abnormal	Model establishment	Parameters		Model performance		Reference
Pork	Intact	835~2500	MSC, derivative	Mahalanobis distance	PLS	pH		$R_p^2 = 0.90$		Hu et al. (2012)
Pork	Intact	400~1395	MSC, derivative	PCA	PLS	L^*		$R_{cv}^2 = 0.84$		Balage et al. (2015)
						a^*		$R_{cv}^2 = 0.85$		
						b^*		$R_{cv}^2 = 0.74$		
						pH		$R_{cv}^2 = 0.70$		
						WBSF		$R_{cv}^2 = 0.30$		
						IMF		$R_{cv}^2 = 0.22$		
Pork	Intact	350~1100, 1000~2500	SG, SNV	None	PLS	L^*		$R_p = 0.9428$		Wang et al. (2016)
						a^*		$R_p = 0.9321$		
						b^*		$R_p = 0.9536$		
						pH		$R_p = 0.9488$		
						Cooking loss		$R_p = 0.9025$		
Beef	Intact	350~1800	MSC, derivative	Mahalanobis distance	PLS	Aberdeen Angus beef	R_c^2	Limousin beef	R_c^2	Prieto et al. (2011)
						C14:0	0.46	C14:0	0.62	
						C16:0	0.48	C16:0	0.69	
						C16:1	0.48	C16:1	0.69	
						C18:0	0.32	C18:0	0.71	
						*Trans11*C18:1	0.40	*Trans11*C18:1	0.70	
						C18:1	0.46	C18:1	0.76	
						C18:2 n-6	0.70	C18:2 n-6	0.65	
						C20:1	0.62	C20:1	0.71	
						C18:3 n-3	0.27	C18:3 n-3	0.60	
						*Cis*9, *trans*11 C18:2	0.33	*Cis*9, *trans*11 C18:2	0.71	
						C20:4 n-6	0.26	C20:4 n-6	0.12	
						C20:5 n-3	0.26	C20:5 n-3	0.16	
						C22:6 n-3	0.19	C22:6 n-3	0.36	
						SFA	0.40	SFA	0.68	
						MUFA	0.44	MUFA	0.75	
						PUFA	0.16	PUFA	0.64	
						n-6	0.73	n-6	0.45	
						n-3	0.43	n-3	0.12	
						IMF	0.43	IMF	0.75	
Beef	Intact and minced	1000~1799	Mean center, derivative	None	ANN	Minced	Fat	$R_p = 0.972$		Sun et al. (2011)
							Protein	$R_p = 0.949$		
							Water	$R_p = 0.927$		

Table 3 (continued)

Sample	Sample form	Wavelength range (nm)	Pre-treatment method	Elimination of the abnormal	Model establishment	Parameters		Model performance	Reference
						Intact	Fat	$R_p = 0.810$	
							Protein	$R_p = 0.868$	
							water	$R_p = 0.913$	
Beef	Intact and ground	350~1800	SNV, detrending, MSC, derivative	Mahalanobis distance	PLS	Intact	pH	$R_{cv}^2 = 0.62$	De Marchi et al. (2013)
							L^*	$R_{cv}^2 = 0.70$	
							a^*	$R_{cv}^2 = 0.73$	
							b^*	$R_{cv}^2 = 0.60$	
							Aging loss	$R_{cv}^2 = 0.15$	
							Cooking loss	$R_{cv}^2 = 0.38$	
							WBSF	$R_{cv}^2 = 0.34$	
						Ground	pH	$R_{cv}^2 = 0.42$	
							L^*	$R_{cv}^2 = 0.55$	
							a^*	$R_{cv}^2 = 0.52$	
							b^*	$R_{cv}^2 = 0.41$	
							Aging loss	$R_{cv}^2 = 0.12$	
							Cooking loss	$R_{cv}^2 = 0.12$	
							WBSF	$R_{cv}^2 = 0.13$	
Beef	Intact	400~700, 900~2000	SG, derivative, SNV	Leverage	PLS	Tenderness		$R_p = 0.9068$	Tian et al. (2013)
						L^*		$R_p = 0.8854$	
						a^*		$R_p = 0.8362$	
						Cooking loss		$R_p = 0.8453$	
Beef	Intact	400~960, 900~2600	MF, MSC, SNV	None	PLS	Water content		$R_p = 0.88$	Shi et al. (2015)
Beef	Intact	800~2500	Derivative, smooth, SNV, and their combination	None	PLS	Hardness		$R_p = 0.786$ SEP = 8.887 N	Li et al. (2016a)
						Springiness		$R_p = 0.712$ SEP = 0.915 mm	
						Chewiness		$R_p = 0.664$ SEP = 22.117 mJ	
						Adhesiveness		$R_p = 0.694$ SEP = 0.243 N·mm	
Yak meat	Ground	1000~1800	OSC, DT	Mahalanobis distance	PLS	WBSF		$R_p^2 = 0.433$, SEP = 16.312 N	Zhang et al. (2015)
						Cooking loss		$R_p^2 = 0.612$, SEP = 2.643%	
						Press loss		$R_p^2 = 0.672$, SEP = 2.641%	
						L^*		$R_p^2 = 0.737$, SEP = 2.078	
						a^*		$R_p^2 = 0.813$, SEP = 1.669	

Table 3 (continued)

Sample	Sample form	Wavelength range (nm)	Pre-treatment method	Elimination of the abnormal	Model establishment	Parameters	Model performance	Reference
						b^*	$R_p^2 = 0.929$, SEP = 0.816	
						Hue angle	$R_p^2 = 0.868$, SEP = 1.857	
						Saturation index	$R_p^2 = 0.920$, SEP = 1.904	

Abbreviations: ANN, artificial neural network; DT, detrending; IMF, intramuscular fat; MF, median filter; MSC, multiplicative scatter correction; MUFA, monounsaturated fatty acids; OSC, orthogonal signal correction; PCA, principal component analysis; PLS, partial least square; PUFA, polyunsaturated fatty acids; R_c^2, determination coefficient in the calibration set; R_{cv}^2, determination coefficient of cross-validation; R_p, correlation coefficient in the prediction set; SEP, standard error in the prediction set; SFA, saturated fatty acids; SG, Savitzky Golay; SNV, standard normal variate; WBSF, Warner-Bratzler shear force

each ingredient in a pixel-wise manner, which makes the prediction results more intuitionistic. As hyperspectral images contain high-dimensional data, a simplified version derives from it, namely multispectral imaging (MSI), which uses a few (generally less than 10) wavebands that are extracted from fundamental datasets of hyperspectral images. Instead of obtaining continuous spectra in HSI system, discrete spectral data are acquired by MSI technology.

A typical HSI system is shown in Fig. 2a, which mainly consists of a charge-coupled device (CCD) camera and its control unit, an imaging spectrograph, a specially assembled light unit, a conveyer belt operated by a stepper motor, data acquisition software, and a computer. When acquiring spatially resolved hyperspectral scattering images, the light source is replaced by a point illuminant source (usually use a quartz tungsten halogen lamp and an optical fiber) (Fig. 2b) (Peng and Lu 2008). A more detailed description of the optical fundamentals of HSI and the most recent advances in the configurations was given by Huang et al. (2014a). The methods for acquiring and analyzing spectral images and calibrating spectral imaging systems were summarized by Qin et al. (2013).

As the original images contain thousands of multidimensional data distributed over the measured area, further analyses are needed by means of chemometric tools. For the spatially resolved hyperspectral images, they undergo the following processing as shown in Fig. 3a. After acquisition, scattering profiles are fitted using Lorentzian or Gompertz function (Lu and Peng 2006). Then Lorentzian parameters (a, asymptotic value; b, peak value; c, full width at $b/2$; d, slope) or Gompertz parameters (α, asymptotic value; β, upper value, ε, full scattering width; δ, slope) are acquired and formed multiple "characteristic spectra," which can be used to characterize the sample properties. Figure 3a shows the fitting process using Lorentzian function, and parameters a, b, and c at each wavelength were extracted. For the reflectance information, the step-by-step analysis procedure is shown in Fig. 3b. After acquisition of meat images at wavelength λ_1 to λ_n, image correction, image segmentation, and range of interest (ROI) selection are conducted. Then spectral data are extracted from the ROI and used for model establishment (ElMasry and Nakauchi 2016). A more detailed introduction about the analysis procedure was given by Iqbal et al. (2014) and Feng and Sun (2012).

The applications of HSI technique cover various agricultural products, such as meat and meat products, fish, fruit, vegetables, and grain. It was verified to be capable of accomplishing various routine inspection tasks. Here, we provide a specific summary about the applications of hyperspectral scattering profiles and reflectance information in evaluation of quality and safety attributes and classification of fresh red meat. It is hoped that the review would contribute to an in-depth understanding of the hyperspectral application in meat industry.

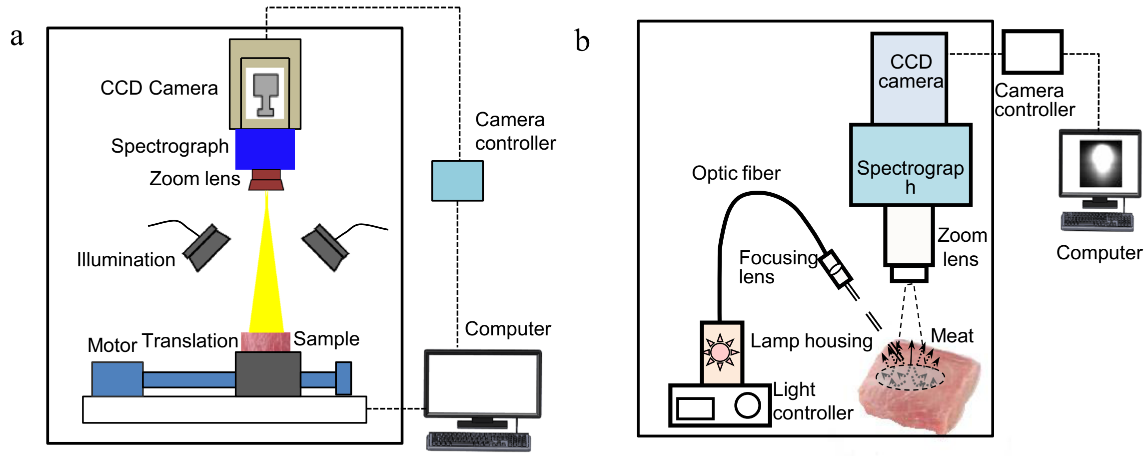

Fig. 2 Schematic of a hyperspectral imaging system: **a** for reflectance, **b** for scattering

Quality Analysis Using HSI

The potential of scattering profiles for quality inspection was explored and significant correlations were found. An early paper on this topic was given by Wu et al. (2010), in which hyperspectral scattering technique was employed to predict beef tenderness, pH, and color (L^*, a^*, and b^*). MLR models were established based on Lorentzian parameters a and b with correlation coefficient of cross validation (R_{cv}) of 0.86, 0.86, 0.92, 0.90, and 0.88. Subsequently, the authors investigated its capacity to predict tenderness and color (L^*, a^*, and b^*) of 7-day aged beef samples. Lorentzian parameters $a\&b\&c$ at feature wavelengths were used to build MLR models with R_{cv} of 0.91, 0.96, 0.96, and 0.97 (Wu et al. 2012a). Later, Tao et al. (2012) turned to the study of tenderness prediction for pork. Likewise, MLR models based on individual parameter and combined parameters of $(b-a)$, $(b-a)\times c$, $(b-a)\ /\ c$ and "$a\&b\&c$" were developed and compared. The results showed that the models using parameters a, b, $(b-a)$, and $(b-a)\ /\ c$ performed better with R_{cv} of 0.831, 0.860, 0.856, and 0.930, respectively. Meanwhile, the authors also applied Gompertz function and found that integrated parameter $\alpha\&\beta\&\varepsilon\&\delta$ was superior to individual parameter with R_{cv} of 0.949 for pork tenderness (Tao and Peng 2014).

Researches based on reflectance spectra are more than those with scattering profiles, especially when spatial distribution of quality attributes is needed. An early trial was reported by ElMasry et al. (2011, 2012), who realized non-contact measurement of WHC, surface color, pH, and tenderness of fresh beef. Image processing algorithms were applied to each pixel, thus the distribution of components content can be visualized by producing pseudo-color images in which different colors represent different concentrations. Subsequently, the authors developed a laboratory-based push-broom HSI system in the range of 900~1700 nm for determination of major chemical compositions in beef (ElMasry et al. 2013). PLS models were built, yielding R_p^2 of 0.89, 0.84, and 0.86 for water, fat, and protein content, respectively. In another study, Barbin et al. (2013d) compared the capability of HSI technology and computer vision imagery for predicting beef tenderness. The results indicated that the PLS model using spectral information alone performed better than that using features extracted from computer vision images and R_{cv}^2 increased to 0.75 when combining information together. In addition to using only the spectral information, Liu and Ngadi (2014) proposed a new method by calculating the proportion of IMF content fleck areas at critical wavelengths to predict IMF content in pork. Comparison of PLS and MLR models indicated that PLS model outperformed other methods with R_p^2 of 0.97. Based on his research, Huang et al. (2016) reported another approach to predict the IMF content and marbling score (MS) of fresh, frozen, and frozen-thawed pork. Comparison of prediction results using raw and Gabor-filtered spectra showed that Gabor filter technique could extract critical features of IMF and MS, but more work is needed to improve the prediction accuracy of frozen-thawed pork. Subsequently, the authors compared three different processing methods (Gabor filter, gray level co-occurrence matrix (GLCM), and wide line detector) for determination of IMF content of rib end, and the best model was obtained based on the Gabor-filtered mean spectra (Huang et al. 2017). In addition, the application of HSI for marbling evaluation was also conducted by Velasquez et al. (2017). The authors firstly attempted the decision tree method for agricultural product, and satisfactory result was obtained with a classification error of 0.08% in the building stage.

In addition to these applications on pork and beef, numerous studies have also been conducted for the prediction of lamb. The potential of HSI in the NIR range of 900~1700 nm was firstly investigated by Kamruzzaman et al. (2012b) for prediction of chemical compositions in lamb meat. Six feature wavelengths were selected and used to create PLS models. R_p^2 of 0.84, 0.87, and 0.82 were obtained for

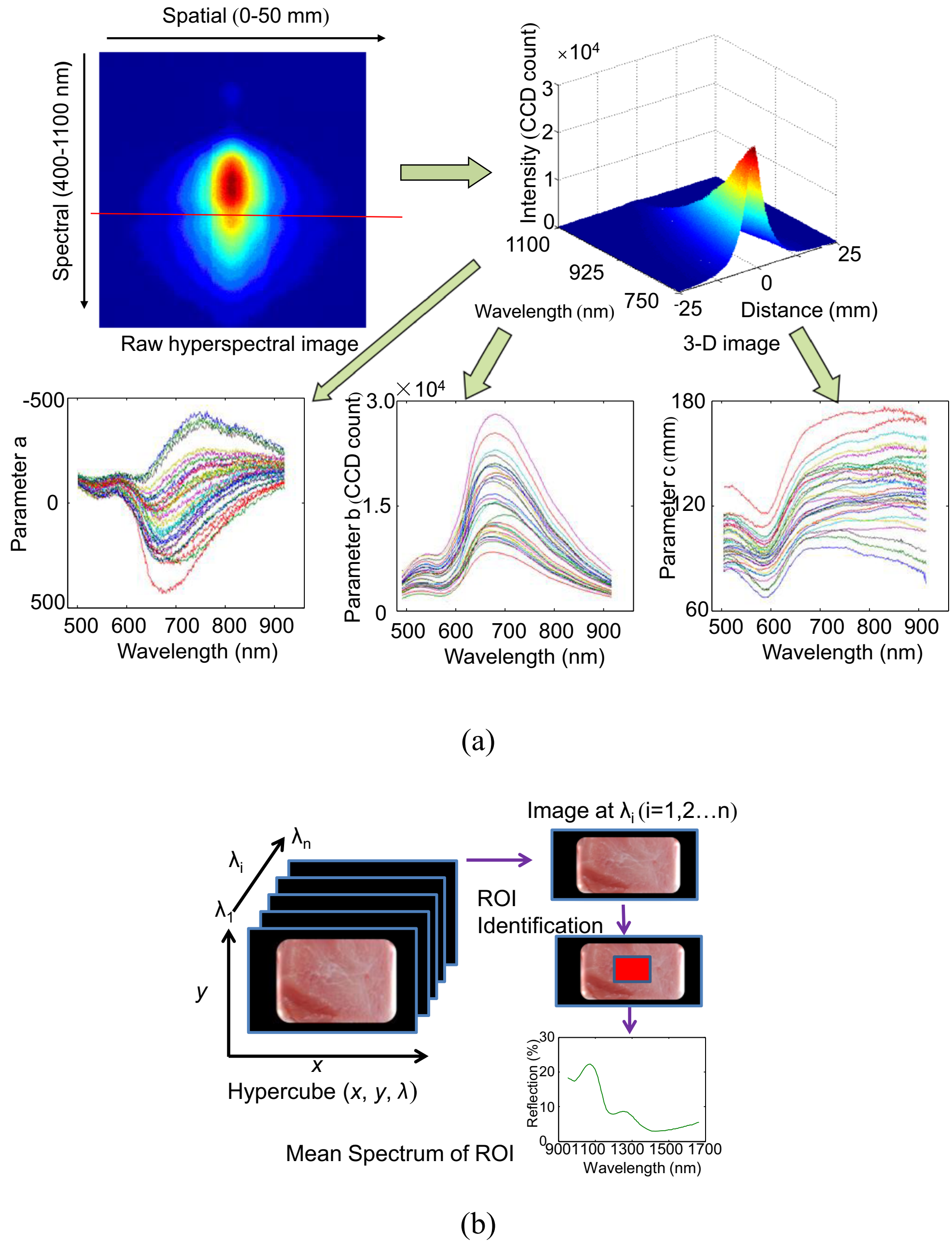

Fig. 3 Main analysis procedure for hyperspectral images: **a** for scattering, **b** for reflectance

water, fat, and protein, which confirmed its prediction capability for lamb. Further, based on the same instrument, the authors continued to exploit its capacity in predicting other quality attributes. Satisfactory result was obtained for L^* with R_{cv}^2 of 0.91, and reasonable good prediction performance was achieved for pH and drip loss with R_{cv}^2 of 0.65 and 0.77, respectively (Kamruzzaman et al. 2012c). More recently, the authors firstly attempted to use HSI technique for determination of both instrumental and sensory tenderness in lamb. PLS models were built with R_{cv} of 0.84 for WBSF and 0.69 for sensory tenderness. Although the models needed further improvement, it was still considered to be an interesting screening tool to quickly categorize meat into tender and tough classes (Kamruzzaman et al. 2013a). Meanwhile, the capability of hyperspectral images in the range of 400~1000 nm was also examined. Kamruzzaman et al. (2016a) conducted an exploratory study on real-time monitoring of WHC in red meat. Eight characteristic wavelengths were selected to build LS-SVM model, which gave a good prediction result with R_p^2 of 0.93. All the aforementioned results have demonstrated the great potential of HSI technology for lamb quality assessment, which also laid foundation for the development of multispectral equipment.

Besides the laboratory study, HSI technology was also implemented under commercial conditions for real-time detection of quality attributes. Konda Naganathan et al. (2016) developed a prototype on-line system to collect images of ribeye muscle on hanging beef carcasses in beef packing plants. Experimental results showed that principal component analysis (PCA) combined with Fisher's linear discriminant (FLD) gave the best performance with tender certification accuracy of 86.7% and accuracy index value of 66.8%. The results were better than spectroscopic system and beefcam, which was developed by Colorado State University for tenderness prediction. In another study reported by Craigie et al. (2017), the possibility of HSI technology for lamb quality assurance within a processing plant environment was evaluated. Lamb *M. longissimus lumborum* were collected over two sampling years to predict FA compositions and pH. This research also highlighted the importance of ongoing calibration and validation for improving model robustness.

Safety Analysis Using HSI

The ability of spatially resolved hyperspectral scattering profile for spoilage evaluation has already been investigated and satisfactory results were found. Peng et al. (2011) conducted a study on using two-parameter Lorentzian function to fit the spectral scattering profiles at individual wavelengths. Then MLR model was built to relate the combined Lorentzian parameters and TVC content, which yielded a good prediction result with R_p^2 of 0.95. Three-parameter Lorentzian function was then employed by Tao et al. (2012) to determine the *Escherichia coli* contamination in pork. Individual parameter *a* and combined parameters "*a*&*b*&*c*" gave high R_{cv} of 0.877 and 0.841, respectively. Subsequently, the authors explored the feasibility of modified Gompertz function to extract the scattering characteristics of pork. The comparison of individual Gompertz parameter (α, β, ε, and δ) and the combined one (α&β&ε&δ) showed that better result was obtained for *E. coli* based on the combined one with R_{cv} of 0.939 (Tao and Peng 2014). A similar conclusion was given by Song et al. (2014) who compared the capability of Gompertz and Lorentzian function for fitting the scatter profile of pork. In this work, TVC was well predicted using the combined Gompertz parameter with R_p of 0.92. Followed by the research, Tao et al. (2015) proposed an optimal approach to detect low levels of TVC contamination in beef. Based on the individual and combined Lorentzian parameters, three modeling methods which consisted of PCR, PLS, and back propagation neural network (BPNN) were applied, and the BPNN model was deemed the best with R_p of 0.90. The results also verified the preponderance of combined parameters in predicting safety attributes in meat. However, as we know, no work has been published on prediction of safety attributes in lamb using the scattering profile.

Based on reflectance spectra, a few studies have been conducted to quantify TVC. Barbin et al. (2013a) explored the feasibility of HSI in the range of 900~1700 nm to determine TVC and psychrotrophic plate count (PPC) in pork stored in aerobic conditions at two temperatures (0 and 4 °C). PLS models were established which gave R_p^2 of 0.86 and 0.89. By applying the models to each pixel in the images, spatial visualization maps were produced from which the magnitude of microbial contamination in the sample could be observed. Huang et al. (2013) reported another study by using light diffuse reflectance for accurate determination of TVC. Good agreement was achieved with R_p^2 of 0.8308 when combing spectral variables and image variables, which showed superior to any single information.

Besides using HSI technology, there are plenty of studies conducted on using MSI technology for contamination assessment. Dissing et al. (2012) used a rapid MSI device for spoilage detection of pork stored at different temperatures (0, 5, 10, 15, and 20 °C) and package types (aerobic and modified atmosphere). The TVC was predicted with SEP of 7.47%, which demonstrated the potential of the setup for microbial count prediction in minced meat. Subsequently, another study was carried out by Panagou et al. (2014), who used the MSI technology for microbial count determination in aerobically packaged beef at different storage temperatures (0, 4, 8, 12, and 16 °C). Average estimation deviations of 11.6, 13.6, and 16.7% were achieved for *Pseudomonas* spp., *B. thermosphacta*, and TVC, respectively. Besides, the authors also classified samples into three classes according to TVC (< 5.5, 5.5–7.0, and > 7.0) with accuracy rate of 80.0%. More attention should be paid to the color stability for further application of MSI technology in microbiological monitoring. Recently, Tsakanikas et al. (2016) extracted contamination "signature" spectra for TVC contamination assessment using MSI technique. Aerobically packaged beef stored at 2, 8, and 15 °C were discriminated into two classes based on TVC with a threshold of 2 $\log_{10}$CFU/g (colony forming units, CFU). The classification accuracy was 80.8%, and quantitative analysis result was determination coefficient in the calibration set (R_c^2) = 0.98, which verified the existence of contamination signature spectra.

With regard to TVB-N, Li et al. (2012) designed a portable device based on MSI technique for real-time detection of TVB-N in intact pork. The device consisted of single-chip micro-computer control unit, light source unit, image acquisition system, data processing unit, and liquid crystal display unit. Combined with the self-developed software, the device could accomplish detection in less than 10 s. More recently, Huang et al. (2015) developed a MSI system based on three characteristic wavelengths (1280, 1440, and 1660 nm). GLCM was employed to extract feature variables from the images, and BPNN adaptive boosting method was proposed for model establishment with R_p of 0.8325. Their work indicated that the MSI system was capable of predicting TVB-N content with reasonable result and the research would facilitate its practical usage in meat industry. Instead of using a few wavelengths, Li et al. (2016b) adopted a 650-nm laser and acquired scattering images for freshness monitoring. Samples were divided into fresh, secondary fresh, and stale based on their TVB-N and TVC contents. Then GLCM was used to extract the texture features and qualitative model was built with discrimination accuracy of 100%.

Apart from TVB-N, other attributes related with freshness were also trialed using HSI technology. A laboratory investigation on predicting biogenic amine index (BAI) value in pork, which are products of bacterial growth and metabolism, was reported by Cheng et al. (2016a). Likewise, they extracted characteristic wavelengths using regression coefficient for model development, and excellent MLR model was built with R_p^2 of 0.957. However, the authors pointed out that the determination of BAI was based on the physiochemical changes related with BAI generation rather than a direct determination of its content. The authors also reported a further study on another important attribute K value, which was an indicator calculated based on the adenosine triphosphate (ATP) related compounds (Cheng et al. 2016b). In their work, spectral information and texture data were extracted by GLCM and fused by the intermediate level fusion (ILF) method, which was known as the integration of the feature variables from each sensor (Huang et al. 2013). The comparison of results showed that the fused data performed better than any single data with an improvement of 17.5%. For a more condensed overview of current trends, these applications are further summarized in Table 4.

Meat Classification Using HSI Technology

Similar with NIRS technology, classification of meat based on HSI technology also relies on spectral differences as well as various discriminant analysis methods. Liu et al. (2010) used image texture features to differentiate four main levels of pork quality (RFN, PFN, PSE, and RSE). Spectral features were extracted from Gabor-filtered and raw images and then compressed into principal components (PCs) using PCA. The linear discrimination analysis (LDA) model yielded an average accuracy of 84 ± 1% by five "hybrid" PCs, which were created by combining PCs from raw and Gabor-filtered images. Another type of HSI system in the NIR spectral range of 900~1700 nm was employed by Barbin et al. (2012a) to categorize meat with different quality. The author used a "dancing pixels" method to select ROI, which could exclude interfering information and acquire characteristic spectra. Then PCA was conducted based on six significant wavelengths with the accuracy of 96% for PSE, DFD, and RFN meat. The study also laid the foundation to the further introduction of MSI instrument for meat quality assessment.

The potential of HSI technology for the identification of meat species was also carried out to prevent meat fraud or adulteration. Kamruzzaman et al. (2012a) combined HSI, multivariate analysis, and image processing to identify pork, beef, and lamb. Partial least square discrimination analysis (PLS-DA) models were established based on six important wavelengths with an overall classification accuracy of 98.67%. Then the authors exploited its possibility for quantification of adulteration in minced lamb (Kamruzzaman et al. 2013b). Minced pork in the range of 2~40% (*w*/*w*) was added into lamb at 2% increments. MLR model based on four feature wavelengths yielded a satisfactory result with R_{cv}^2 of 0.98. The visual distribution map showed obvious spatial variation between different adulteration levels. More recently, the authors tested the aptitude of HSI in tandem with machine learning for detection of chicken adulteration in minced beef (Kamruzzaman et al. 2016d). PLS models were built based on reflectance, absorption, and Kubelkae-Munck spectra with R_p^2 of 0.97, 0.97, and 0.96, respectively. Another study was reported by Ropodi et al. (2015) who used MSI to detect minced beef substituted with pork and vice versa for the first time. A 10% adulteration with pork in beef and vice versa were identified and recognized as the quantitative detection limit. An independent validation indicated that the PLS-DA model could discriminate all the pure and adulterated samples of nine adulteration levels correctly. Further, the authors evaluated its possibility in detecting horsemeat adulteration in minced beef (Ropodi et al. 2017). The independent test yielded an overall correct classification of 95.31%, which was worse than previous study (Ropodi et al. 2015) due to the influence of color changes during storage.

Other authenticity issues, such as the discrimination of fresh and frozen-thawed meat, were conducted Barbin et al. (2013c). Based on the optimal wavelengths that are related to the main chemical changes caused by freezing and thawing processes, PLS-DA models were established. Then a set of independent samples were used to validate the models and achieved an overall correct classification of 100%. More recently, in another study, the feasibility of MSI for identification of water-injected beef was conducted by Liu et al. (2016). PLS model was built based on spectral data and feature information extracted from RGB (red, green, blue) data with R_p = 0.946, which was better than that using only spectral data (R_p = 0.923).

Raman Spectroscopy

RS is another form of analytical vibrational spectroscopy, and it is an obvious inelastic scattering effect discovered by C.V. Raman in 1928 (Raman and Krishnan 1928). When the

Table 4 The recent applications of HSI technique for red meat

Sample	Information feature	Wavelength range (nm)	Treatment methods	Attributes		Model performance	Reference
Pork	Reflectance	400~1100	GLCM, PCA	Tenderness		Accuracy rate = 80.77%	Chen et al. (2010)
Pork	Reflectance	400~1000	PLS, ANN, LS-SVM	TVC		$R_p^2 = 0.9426$	Wang et al. (2010)
Pork	Reflectance	400~1000	PLS, MLR	TVC		$R_p = 0.886$	Tao et al. (2010)
Pork	Reflectance	470~1000	SG, MSC, SNV, PLS	pH		$R_p = 0.79$	Zhang et al. (2012a)
				TVB-N		$R_p = 0.90$	
Pork	Reflectance	900~1700	MSC, SNV, PLS, PLS-DA	L^*		$R_p^2 = 0.90$, RMSEP = 1.63	Barbin et al. (2012b)
				a^*		$R_p^2 = 0.72$, RMSEP = 0.78	
				b^*		$R_p^2 = 0.85$, RMSEP = 0.50	
				Chroma		$R_p^2 = 0.82$, RMSEP = 0.74	
				Hue angle		$R_p^2 = 0.81$, RMSEP = 3.38	
				pH		$R_p^2 = 0.90$, RMSEP = 0.09	
				Drip loss		$R_p^2 = 0.79$, RMSEP = 1.34%	
Pork	Reflectance	900~1700	PLS	Fat		$R_{cv}^2 = 0.95$	Barbin et al. (2013b)
				Protein		$R_{cv}^2 = 0.88$	
				Water content		$R_{cv}^2 = 0.87$	
Pork	Reflectance	300~1100	PLS	Water content		$R_p = 0.924$	Liu et al. (2013)
Pork	Reflectance	900~1700	First derivative, Gabor filter, GLCM	Intramuscular fat content		$R_c = 0.89$, $R_p = 0.89$, $R_{cv} = 0.86$	Huang et al. (2014b)
Pork	Scatter	400~1000	Lorentzian parameter, Gompertz parameter, moving average method, SMLR	TVC (b)		$R_p = 0.94$	Tao et al. (2015)
				TVC (β)		$R_p = 0.93$	
Pork	Scatter	400~1000	Gompertz parameter, SVM, PLS-DA, Bayesian analysis	Quantitative prediction	L^*	$R_p = 0.92$	Zhang and Peng (2016)
					pH	$R_p = 0.94$	
					TVB-N	$R_p = 0.95$	
					TVC	$R_p = 0.96$	
					Pseudomonas spp.	$R_p = 0.93$	
				Qualitative identification	Accuracy (PLS-DA)	85.7%	
					Accuracy (Bayesian)	92.9%	
Pork	Reflectance, absorption	400~1000	SG, MSC, PLS, SAI	Water content		$R_p^2 = 0.952$	Ma et al. (2016)
Beef	Scatter	922~1739	Lorentzian function, PCA	Accuracy rate (tough)		83.3%	Cluff et al. (2013)
				Accuracy rate (tender)		75.0%	
Beef	Reflectance	400~1000	GLCM, PCA, GA, LD, SVM	Accuracy rate		94.44%	Zhao and Peng (2015)
Beef	Reflectance	400~1000	SAM, EDM	Intramuscular fat content	SAM	$R_p^2 = 0.95$	Lohumi et al. (2016)
					EDM	$R_p^2 = 0.97$	

Table 4 (continued)

Sample	Information feature	Wavelength range (nm)	Treatment methods	Attributes	Model performance	Reference
Beef	Reflectance	283~863	SSA, SVM	SSF_7	$R_p^2 = 0.3288$	Qiao et al. (2015)
				SSF_{14}	$R_p^2 = 0.2033$	
				pH_7	$R_p^2 = 0.5838$	
				pH_{14}	$R_p^2 = 0.4863$	
Beef	Reflectance	880~1720	MSC, SNV, PCA	Fat	$R_p^2 = 0.99$ RMSEP = 0.73%	Zhao et al. (2017)
				Moisture	$R_p^2 = 0.99$ RMSEP = 0.64%	
Lamb	Reflectance	900~1700	UVE, SPA, CSA	Fat	$R_p = 0.98$	Pu et al. (2014)
				Protein	$R_p = 0.67$	
				Water content	$R_p = 0.92$	
Pork, beef, lamb	Reflectance	380~1000	MSC, SNV, derivative	Water content	$R_c^2 = 0.96$, $R_p^2 = 0.97$	Kamruzzaman et al. (2016c)
Pork, beef, lamb	Reflectance	400~1000	MSC, SNV, PLS, LS-SVM	L^*	$R_p^2 = 0.97$	Kamruzzaman et al. (2016b)
				a^*	$R_p^2 = 0.84$	
				b^*	$R_p^2 = 0.82$	

Abbreviations: ANN, artificial neural network; CSA, clonal selection algorithm; EDM, Euclidian distance measure; GA, genetic algorithm; GLCM, gray level co-occurrence matrix; LD, linear discrimination; LS-SVM, least square support vector machine; MLR, multiple linear regression; MSC, multiplicative scatter correction; PCA, principal component analysis; PLS, partial least square regression; PLS-DA, partial least square discrimination analysis; R_c, correlation coefficient in the calibration set; R_c^2, determination coefficient in the calibration set; R_{cv}, correlation coefficient of cross validation; R_{cv}^2, determination coefficient of cross validation; R_p, correlation coefficient in the prediction set; R_p^2, determination coefficient in the prediction set; RMSEP, root mean square error of prediction; SAI, spectral absorption index; SAM, spectral angle measure; SG, Savitzky-Golay; SMLR, stepwise multiple least regression; SNV, standard normal variate; SPA, successive projections algorithm; SSA, singular spectrum analysis; SSF, slice shear force; SVM, support vector machine; TVB-N, total volatile basic nitrogen; TVC, total viable counts; UVE, uninformative variable elimination sample is exposed to a laser beam, most of the incident photons (99.9999%) undergo Rayleigh scattering (also called elastic scattering), in which case, the incident light energy and scattered energy are not changed. Only a very small part (0.0001%) of incident light produced inelastic Raman signals, in which case, the shift in the energy level between incident and scattered beam is observed (Yaseen et al. 2017). If the photons scattered from molecular centers have greater energy than the exciting radiation, it is called anti-Stokes scattering. Conversely, it is named Stokes scattering (Tao and Ngadi 2017). The change in the energy state in wave number (cm^{-1}) is called Raman shift, which can be defined as "chemical fingerprint" of the samples, and this is the theoretical basis for characterization of structures and qualitative identification of Raman spectra.

A typical RS system consists of a monochromatic light source (usually laser), spectrometer, CCD, optical fiber probe, and computer. After acquisition of Raman spectra, the data are calibrated first, and then ROI is selected. Noise filtering is a necessary step before further analysis as the presence of noise increases the complexity as well as reducing the signal to noise ratio (SNR). There are various digital filter methods, and Savitzky-Golay (SG) smoothing is the widely used one. Fluorescence background interference is another challenge as Raman scattered signals are weak and the presence of strong fluorescence background increases the difficulty in qualitative and quantitative analysis. Several algorithms have been put forward for subtraction of fluorescence background, such as iterated polynomial fitting and adaptive iteratively reweighted penalized least squares (airPLS). Then qualitative analysis is performed based on identification of the spectral peak, which represents the fingerprint of target attributes. Quantitative analysis is done based on the correlation of spectral signal intensity and reference values.

RS has many advantages: (1) Raman bands have a good SNR and they are non-overlapping, thus providing obvious Raman fingerprint of target attributes; (2) no special sample preparation is required and the absence of contact with sample gains its importance in meat analysis; (3) RS technology can complete the analysis in a few seconds, which makes it feasible for real-time detection (Yang and Ying 2011); (4) Raman spectra exhibit well-resolved bands of fundamental vibrational transitions, thus providing a fair amount of molecular structure information of several components (Herrero 2008); and (5) Raman effect is insensitive to water, which is favorable for meat analysis as it contains a high water content of about 75%.

The applications of RS for inspection of meat were relatively less compared with NIRS and HSI techniques. In the last few years, technical progress in spectrometer, detector, and filter technology, combined with the development of innovative chemometric approaches, has triggered the development of RS technology and paved ways for an increasing number of applications. Hence, a summary of recent research progress of RS for quality, safety, and classification of meat is necessary to get a glimpse of current application of RS technology.

Quality Analysis Using RS

The preliminary investigations on the application of RS were carried out by Beattie et al. (2004, 2006, 2008) and Olsen et al. (2007), which demonstrated the feasibility and potential of RS in quality control programs for fresh red meat. However, they all used a bench top instrument with a 785 nm in their studies. To satisfy the requirement of industrial application, a handheld and compact device based on a laser diode emitting light at 671 nm was developed by Schmidt et al. (2009). Then the author investigated its potential in estimating the SF and cooking loss of cooked meat (Schmidt et al. 2013). Raman spectra of raw sheep meat from two different origins (second cross lambs and first cross lambs) were collected and used for build PLS models. The results showed that models based on single origin performed better than that based on the combined one. For the two sample origins, R_c^2 of 0.79 and 0.86 were obtained for SF; 0.79 and 0.83 were achieved for cooking loss, respectively. One reason for this may be due to the offset in spectral background between both sites. Using the same device, Fowler et al. (2014a) conducted a study for the first time to investigate the potential of RS to predict SF of fresh lamb *M. semimembranosus* (topside, whose product identification number is HAM 5077). Based on PLS method, they achieved the best prediction result with R_{cv}^2 of 0.27. The authors also found that tough and tender lamb meat can be discriminated effectively using the intensity of spectral peaks at 826, 853, and 930 cm^{-1}. Besides, given the economic value of the *M. longissimus lumborum* (LL), the authors also conducted a study to predict SF in LL (Fowler et al. 2014b). However, a poor result with R_{cv}^2 of 0.06 was achieved, but they believed that these conclusions were restricted to LL excluded other muscles and traits. Then the authors studied its possibility in predicting IMF and FA in LL. The results demonstrated its potential in prediction PUFA ($R_c^2 = 0.93$), MUFA ($R_c^2 = 0.54$), and SFA that had been adjusted for IMF content ($R_c^2 = 0.54$) (Fowler et al. 2015).

Based on the portable Raman system, studies on predicting quality traits in pork were also carried out. Scheier et al. (2014) used it to predict pH_{45} (pH measured 45 min postmortem), pH_{24} (pH measured 24 h postmortem), L^*, a^*, b^*, drip loss, and SF after 24 and 72 h under real-life conditions in the cooling house. Promising correlations were found for pH_{45}, pH_{24}, and L^* with R_{cv}^2 of 0.65, 0.68, and 0.64; better correlations were built for b^*, drip loss, and SF after 72 h with R_{cv}^2 of 0.73, 0.73, and 0.70. However, the results for a^* and SF after 24 h needed further improvement. Subsequently, the authors tried to measure and predict quality traits of intact muscles at the slaughtering process for the first time (Scheier et al. 2015). Likewise, the prototype handheld Raman device was employed to collect RS of intact muscles 30~60 min postmortem at the veterinarian line of a commercial abattoir. Then PLS models for pH_{35} (pH measured 35 min postmortem), pH_{24}, and drip loss were built with R_c^2 of 0.75, 0.58, and 0.83. The results confirmed the applicability of RS to predict important quality traits, but further improvement should be made in terms of analysis speed and robustness of predictive model. Nache et al. (2016) continued his work and introduced *ant colony optimization* (ACO) metaheuristics to predict pH_{45} and pH_{24} for the first time. The results indicated that information about pH_{45} and pH_{24} was inherently contained in the prerigor and post-rigor Raman spectra. However, further research needed to be conducted as more Raman spectral information about the nature of metabolism was still uncovered.

With respect to beef, few studies were conducted. One study was reported by Bauer et al. (2016) who first used the aforementioned 671-nm Raman system to evaluate SF values of beef. PLS models for beef aged at − 1 and 7 °C were built with R_{cv}^2 of 0.33 and 0.79 at two storage temperatures. Besides, the authors also discriminate the samples into tough and tender with validation accuracy rates of 59~80% according to thresholds between 30 and 49 N. Recently, Nian et al. (2017) made a further study on using RS technology to predict eating quality related with physico-chemical traits of bull beef. Different from the previous studies, homogenized samples from different types of muscle and aging times were used. R_{cv}^2 values of 0.75, 0.77, 0.85, 0.91, 0.70, 0.79, 0.79, and 0.88 for WBSF, cook loss, IMF, moisture, crude protein content, total collagen, hydroxyproline content, and collagen solubility were achieved. In addition, the authors also exploited its capacity to discriminate samples with different ages and muscles; accuracies of 100 and 86.70% were obtained, which demonstrated its application potential.

Safety Analysis Using RS

The employment of Raman spectra to monitor the biochemical and physical changes during storage was investigated by Sowoidnich et al. (2012). In their study, the authors described the aforementioned portable 671-nm Raman sensor system in detail and demonstrated its capacity in discriminating edible from spoiled meat. Argyri et al. (2013) compared the FT-IR spectroscopy and RS for micro-biological and sensory assessment of minced beef samples under different packing conditions (aerobic and modified atmosphere packaging). Several machine learning and evolutionary computing methods were employed and compared, and the genetic algorithm-artificial neural network (GA-ANN) model gave a classification accuracy of 96.15 and 81.08% for fresh and spoiled sample.

Using the surface enhanced Raman spectroscopy (SERS) technique, Zhai et al. (2017) attempted the feasibility to detect salbutamol in muscle tissues and liver. SG smoothing and airPLS were employed to eliminate the noise and fluorescence background. 621, 814, 1253, 1489, and 1609 cm^{-1} were identified as the characteristic peaks and used for monitoring the salbutamol levels. The detection limit for salbutamol in muscle tissues and liver samples was 0.01 and 0.02 mg/kg, and R_p^2 of 0.912 and 0.921 was obtained for quantitative analysis. Their study provided a possible method for evaluation of harmful additives in animal product sample.

Meat Classification Using RS

Few attempts have been carried out for classification of meat using RS technology. Boyaci et al. (2014) proposed a novel method to discriminate beef and horsemeat using RS combined with chemometrics. PCA was conducted on Raman data of pure fat samples and adulterated beef samples with horsemeat in 0, 25, 50, 75, and 100% by weight. The high accuracy, short analysis time, and straightforward sample preparation demonstrated that RS technology can be a potential tool for adulteration recognition. More recently, Biasio et al. (2015) reported another study about using micro-RS to discriminate different meat types including chicken, pork, turkey, beef, horse meat, and mutton. The results indicated that the discrimination between white and red meat was easy to do. However, more sophisticated analysis methods were required when classifying samples within the red meat class as the error rate is up to 15%. As far as the present result is concerned, although useful information to discriminate meat was obtained, much work still needed to be done for industrial meat sorting.

Challenge and Future Trends

Despite the rapid development of NIRS, there are several drawbacks facing this technology. Firstly, the establishment of precise models depends on laborious calibration procedures, which makes it time-consuming and costly at the beginning. Much effort should be taken to relate spectra and reference values and build an accurate model. Besides, the model updating also requires substantial time, energy, and funds. Secondly, the model robustness is a significant challenge for NIRS as it is susceptible to acquisition parameters and environmental conditions. Acquisition parameters such as scanning times, distance between sample and detector, as well as environmental factors such as ambient temperature, humidity, illumination conditions, and sample temperature would influence the spectra collection. Hence, to build a robust model in the presence of variable interferences, much work still needs to be done. Thirdly, the lack of uniformity between optical instruments is another important issue, which makes the calibration models obtained using one device not be readily used on another. The rebuild of models would be heavy work in this case and increase the difficulty in application.

Last but not the least, as the acquired spectral profiles usually contains large amounts of information, hence, elimination of redundant information to reduce multicollinearity problem is necessary. Various algorithms for characteristic wavelengths selection have emerged. However, the feature wavelengths chosen by different methods are not consistent even for the same set of spectra, and the lack of interpretability for some feature wavelengths is another puzzling problem.

With respect to HSI technique, except for the foregoing limitations, there are other barriers that it suffers from. As spectral and spatial information are obtained simultaneously, the high dimensional nature of hyperspectral data bring many barriers in data acquisition and processing. To speed up the image analysis by identifying the most influential wavelengths and eliminating the irrelevant information remains a challenging task. With such massive raw image data, it is difficult for HSI systems to be widely implemented for on-line and real-time application. In addition, the HSI instrument is relatively expensive compared with conventional methods, thus increasing the cost of commercial detection and impeding its broader adoption.

As to RS, which is considered as a fast and convenient method with high sensitivity and fine application prospect, there is still a long way to go. Fluorescence background has been deemed as one of the major factors that limit its applications. Selection of appropriate excitation wavelength and use of fluorescence quenching agent are possible tools to eliminate fluorescence. Other features such as the laser power, scan times, and sample orientation can jeopardize accurate quantification (Yang and Ying 2011). These problems especially the elimination of fluorescence interference issues still need to be further solved and studied for on-line or real-time application.

In fact, some effort has been taken to overcome these difficulties facing the spectral methods. Several recent studies have been conducted as possible solutions in response to these disadvantages. For instance, new algorithms are being proposed to eliminate the undesired effects and noise produced during the data acquisition. Qiao et al. (2015) employed singular spectrum analysis (SSA), which is commonly used for time series analysis, as a pre-processing approach for hyperspectral data. The experimental results indicated that the method could remove the instrument noise effectively and improve model performance. In addition, some academic groups are working on understanding the absorption and scattering behaviors of diffuse reflectance to develop better algorithm for extraction of relevant information, which allows for the removal of various interference. Meanwhile, the manufacturers are working on methodologies to diminish manufacturing variability, which would improve the transfer issues.

However, in spite of such drawbacks, the enhancement in instrumental development in combination with the availability of high-speed computer and the development of appropriate chemometric procedures will facilitate this technique to be dominant in the future. Firstly, with the increasing demand for meat assurance, on-line and real-time detection systems for multiple attributes are in urgent need. These optical systems which could realize an instantaneous knowledge of meat components should be the main future trend and would play a crucial role in increasing the profitability of meat industry. Early efforts have achieved initial successes; however, the implement of on-line inspection still requires more investigation. In fact, on-line measurements have been claimed by a number of studies but rarely perform them. Hence, much effort needs to be taken for further large-scale online studies to verify the reliability and accuracy under industrial processing condition.

Secondly, with the simplification and great diffusion of these spectral methods, efficient portable, handheld, and micro-optical instruments with multifunction and low cost are becoming available, which offers possibility to perform analysis outside from laboratories (Alamprese et al. 2016; Ayvaz and Rodriguez-Saona 2015). The development of low-cost, miniature, fit-for-purpose detection device for meat has the potential to completely change the conventional instrumentation lifecycle. Once implemented, the easy-to-use device directly at the point of interest (e.g., supermarket, farmer's market, selling point, and restaurants) should be undoubtedly a guarantee for the public.

Thirdly, one should also bear in mind that both hardware system with good performance and efficient chemometrics tools are the precondition and foundation of obtaining a robust model. Hence, to develop instruments with higher sensitivity and resolution and to improve the algorithm stability would be research focus for the years to come. For example, for RS technology, the development of fast detectors to separate fluorescence and Raman scattering in time is expected to avoid fluorescence interference, and superconducting nanowire single-photon detector may be one alternative.

In addition, as meat is a complicated sample and single-inspection method may acquire limited information, it would be interesting to combine spectral technology and other emerging technologies to make full use of multivariate information and realize comprehensive evaluation of meat. In fact, some scholars have been working in this direction. Barbin et al. (2013d) developed PLS models to predict slice SF of pork by combining the spectral information collected by HSI system and image features acquired by a computer vision system. A result with $R_{cv}^2 = 0.75$ was obtained, which was better than using any individual information. Huang et al. (2014) conducted another study to evaluate freshness using NIRS, computer vision, and electronic nose techniques. An R_p^2 of 0.9527 was obtained based on the integrated information, which showed superiority of multidata fusion technology. Similarly, Li et al. (2015) integrated HSI technology and colorimetric sensor to predict TVB-N content in pork using a non-linear data fusion method and an R_p of 0.932 was achieved.

Conclusion

This review summarized the recent progress of spectral methods and techniques (NIRS, HSI, and RS) in rapid determination of quality (color, pH, tenderness, WHC, drip loss, cooking loss, fat, protein, water content, FA, etc.), safety (mainly TVB-N and TVC), and classification in fresh red meat (pork, beef, and lamb). The results from different studies may have some difference due to the influence of external factor, such as instrument performance and statistical methods employed. In general, these promising results have demonstrated the great potential for application in meat industry. All these advantages offered by spectroscopic methods and techniques open a wide range of possibilities to act as an adequate tool in the meat industry.

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Compliance with Ethical Standards

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Ethical Approval This article does not contain any studies with human participants or animals performed by any of the authors.

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