Comprehensive REVIEWS in Food Science and Food Safety

Developments and Challenges in Online NIR Spectroscopy for Meat Processing

Y. Dixit, Maria P. Casado-Gavalda, R. Cama-Moncunill, X. Cama-Moncunill, Maria Markiewicz-Keszycka, P. J. Cullen, and Carl Sullivan

Abstract: Meat and meat products are popular foods due to their balanced nutritional nature and their availability in a variety of forms. In recent years, due to an increase in the consumer awareness regarding product quality and authenticity of food, rapid and effective quality control systems have been sought by meat industries. Near-Infrared (NIR) spectroscopy has been identified as a fast and cost-effective tool for estimating various meat quality parameters as well as detecting adulteration. This review focusses on the on/inline application of single and multiprobe NIR spectroscopy for the analysis of meat and meat products starting from the year 1996 to 2017. The article gives a brief description about the theory of NIR spectroscopy followed by its application for meat and meat products analysis. A detailed discussion is provided on the various studies regarding applications of NIR spectroscopy and specifically for on/inline monitoring along with their advantages and disadvantages. Additionally, a brief description has been given about the various chemometric techniques utilized in the mentioned studies. Finally, it discusses challenges encountered and future prospects of the technology. It is concluded that, advancements in the fields of NIR spectroscopy and chemometrics have immensely increased the potential of the technology as a reliable on/inline monitoring tool for the meat industry.

Keywords: chemometrics, meat, near-infrared spectroscopy, on/inline, probe

Introduction

Meat is one of the most desired food products due to its balanced nutritional nature, containing crucial levels of protein, vitamins, minerals and micronutrients and contributing to our growth and development (FAO). It is consumed in a large variety of forms such as roasted meat, fried meat, meat balls, sausages, and many more. Meat quality and its authenticity however, has emerged as an important issue over the past decade when several major events regarding meat adulteration were discovered (Lohumi and others 2015). Food quality has since been one of the most critical considerations with regard to consumer perception, with consumers expecting manufacturers and retailers to provide products of high quality. The increasing awareness necessitate the use of reliable techniques to monitor and evaluate the quality of food (Cen and He 2007; Pan and others 2016).

Near-Infrared spectroscopy has been identified as a valuable and cost-effective tool for estimating various meat quality parameters as well as detecting adulteration. NIR spectroscopy provides many advantages when compared to traditional methods (proximate analysis, HPLC, GC, MS) which includes; speed of analysis, nondestructive and noninvasive measurement, little or no sample preparation, noncontact technique and several others (Zamora-Rojas and others 2012; Salguero-Chaparro and others 2013; De Marchi and others 2017), making NIR spectroscopy suitable for on/inline applications within a processing plant.

NIR measurements for meat products can be performed in 4 different modes: (a) transmission, (b) reflectance, (c) interactance, and (d) transflectance. Transmission mode for example, can be used to detect transparent (liquid) material in minced meat samples or meat pastes, for example, water content and fecal or rumen contamination. Reflectance mode, the most common utilized for meat samples, is the least penetrating mode and can detect adulteration and chemical composition of minced, whole or dried meat samples. Interactance mode detects the reflected energy from deep within the sample while excluding any surface reflectance, which for example can be useful for monitoring vacuum packed meats such as frozen beef or pork while excluding the reflectance from the packaging material. Transflectance mode is designed for measuring thin samples such as ham slices (Nicolai and others 2007; Ozaki Y and others 2007). Each mode has its advantages and disadvantages depending upon the sample geometry and surrounding environment to analyze, therefore one needs to consider all aspects prior to analysis.

Chemometrics plays an important role in extracting useful information from NIR spectra. Chemometrics utilizes various multivariate techniques to build models with the use of reference chemical data obtained through other analytical techniques. Numerous chemometric techniques have been employed by scientists in the area of NIR spectroscopy of meat products (Kamal and

CRF3-2017-0039 Submitted 2/13/2017, Accepted 7/13/2017. *Authors are with School of Food Science and Environmental Health, Dublin Inst. of Technology, Dublin 1, Ireland. Author Cullen is also with Dept. of Chemical and Environmental Engineering, Univ. of Nottingham, UK. Direct inquiries to author Dixit (E-mail: yash.dixit@mydit.ie).*

doi: 10.1111/1541-4337.12295

Karoui 2015; Tajammal Munir and others 2015). In the past few years, various studies have been conducted on the application of NIR spectroscopy for online monitoring of meat products. However, sample heterogeneity, model robustness and several external factors can pose limitations to the inline application of the technology on an industrial level. Nevertheless, advancements such as high standoff distances, multipoint NIR spectroscopy, concurrent measurements, and low spectral acquisition time have illustrated a bright future for inline NIR spectroscopy.

Previous reviews have been published on the online applications of NIR spectroscopy for food production (Porep and others 2015), however the application of NIR spectroscopy has become extremely diversified and product specific, making it difficult to compile a review covering all food products. Nowadays, NIR spectroscopy instruments are specifically designed for meat products taking into consideration their physico-chemical properties; for example, the high susceptibility of meat to microbial spoilage requires a system with very low spectral acquisition time. In the current review, an emphasis has been given to the studies published in the last decade or so. This article gives a brief description about the theory of NIR spectroscopy, system configurations and their relevance followed by its application on meat and meat products analysis. A detailed discussion is provided on the various studies regarding applications of NIR spectroscopy and specifically for online monitoring of meat and meat products, system considerations along with their advantages and disadvantages. Additionally, a brief description has been given about the role of chemometrics in the mentioned studies. Finally, a discussion is provided about the challenges encountered and future prospects of the technology for inline applications.

NIR Spectroscopy

NIR system setup

A typical NIR system consists of the following main components: light source, spectrophotometer and a computer for data acquisition. The light source illuminates the sample, which is then reflected (reflectance mode), transmitted (transmittance mode) or diffused reflected (interactance mode) followed by its detection via an interferometric or a dispersive system (Nicolai and others 2007). The spectrophotometer mainly consists of an interferometer, a prism, a diffraction grating or any similar optical device and a detector; the optical device allows light of only a particular range of wavelengths or a single wavelength to pass through to the detector. Finally, the detector sends the data acquired from the NIR spectra to the computer for further analysis. There are different types of light sources and additional accessories which can be used. Detailed discussions about NIR instrumentation can be found elsewhere (Osborne and others 1993).

NIR region

The NIR region covers the wavelength range from 780 to 2500 nm. The absorption bands are mainly overtones and combinations of fundamental vibrations (Blanco and Villarroya 2002). The spectral signature produced by various meats are different depending upon their chemical composition (Figure 1). Absorption bands observed in the NIR region at 948 and 1448 nm are due to O-H second and first stretching overtones respectively, and are related to moisture content in samples. Moreover, the absorption band at 1928 nm is a combination of O-H stretching and O-H deformation which is also related to moisture content (Cozzolino and Murray 2002; Ortiz-Somovilla and others 2007; Morsy and Sun 2013). Absorption bands related to fat or fatty acids are observed at 920 and 1200 nm (C-H 3rd and 2nd stretching overtone). C-H 1st stretching overtones are observed at 1716 and 1758 nm and their combination tones are observed at 2136, 2298, and 2346 nm which are also related to fat or fatty acid content. Protein content is related to N-H overtones which are observed at 1086, 1187, 1510, 1690, and 2265 nm (Park and others 2001; Morsy and Sun 2013).

System configurations

This section is focused on NIR reflectance spectroscopy as reflectance is the most commonly used mode for meat products. NIR measurements are greatly affected by the positioning of the probes, standoff distances, illuminating spot size and sample geometry (bed-depth variations, smooth or mirror like surface and varied shapes). Probe positioning is vital in order to receive the diffused reflected light back to the detector. When light illuminates the sample, 2 types of reflections are produced; diffused and specular (direct scattering). Specular reflection does not contain any chemical information and it may be minimized by probe positioning, instrument design and sample geometry (Rinnan and others 2009). Bed-depth variations during NIR scanning produces baseline shifts, for example, beef cuts of diverse thicknesses in a processing line. Baseline shifts are produced due to different amount of diffused light reaching the detector because of a change in the effective path length and also due to asymmetric sample geometry. Up to recently, standoff distances used for NIR measurements were in the range of 1.5 to 2.5 cm, increasing distances beyond these was challenging as defocusing occurs (Osborne and others 1993). The use of high powered halogen light sources makes possible to use higher stand-off distances in the range of 30 cm or more. However, the amount of heat energy produced by the halogen source may not be feasible for heat liable materials. The introduction of collimators is a solution to this issue as they can be fitted with fiber optic probes and operate up to 4 cm stand-off distances producing far less incident heat energy on the samples when compared to a direct halogen lighting. The size of the illuminating spot defines the area to be scanned. Single point spectroscopy scans only a small portion of the sample, which could be disadvantageous when analyzing heterogeneous products such as meat. Multipoint NIR systems overcomes this limitation by scanning simultaneously different areas of the sample (Dixit and others 2016b). Smooth or mirror like surfaces produce specular reflection, therefore reflectance mode is not appropriate for certain samples such as less viscous meat pastes or meat juices. Interactance and transflectance modes could be useful in case of such samples. For samples with different shapes such as meat balls, single point spectroscopy would scan only a small portion and would also produce reflections in all directions depending upon the probe positioning. In such case, the use of multipoint spectroscopy along with a light diffuser could be useful. A light diffuser would produce multiple bounces of the reflected light from the sample and increase the amount of diffused reflected light going back to the detector. Apart from these system considerations, baseline shifts (multiplicative effects) and nonlinearities can be largely eliminated with the use of appropriate preprocessing techniques which are discussed in section "Preprocessing techniques."

Meat Analysis Over the Years

The potential of NIR spectroscopy has been identified as a quality monitoring tool by the meat industry. Various studies have been conducted over the years illustrating the capabilities of this technique including hyperspectral imaging (HSI). Hoving-Bolink and

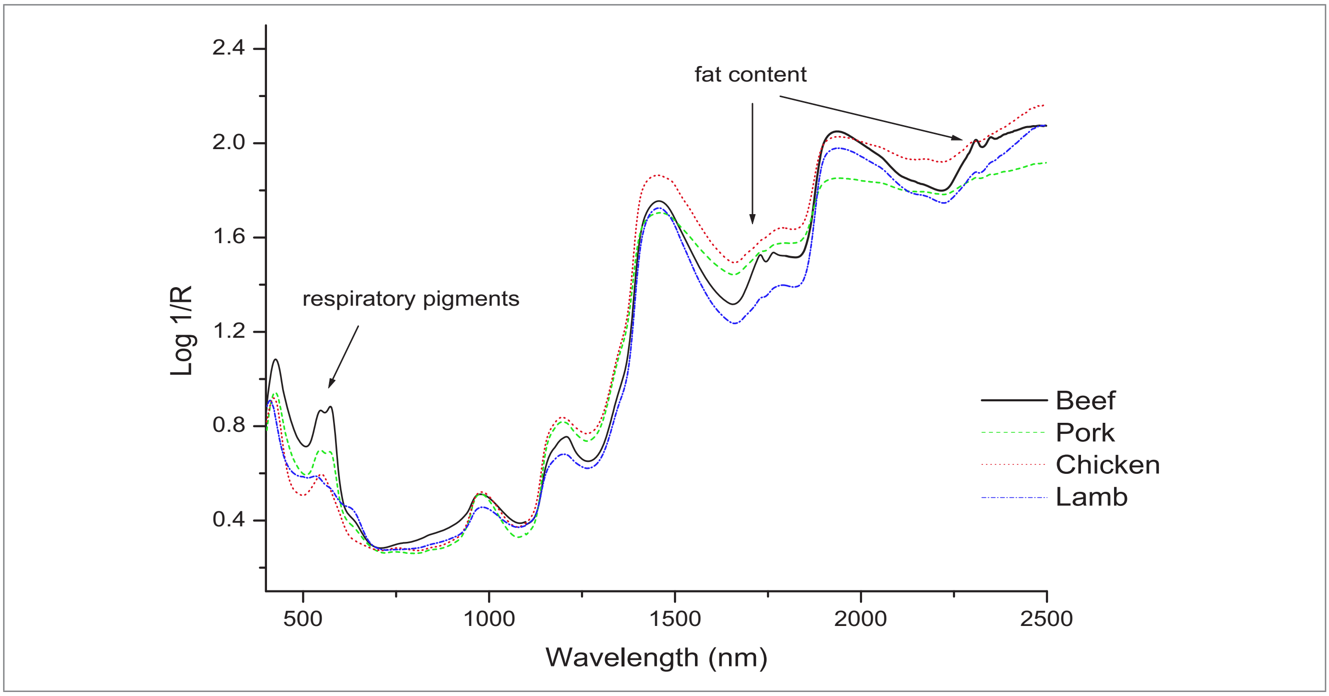

Figure 1–Visible and NIR spectra of beef, pork, chicken and lamb meat, adapted from: (Cozzolino and Murray (2004)).

others (2005) used NIR spectroscopy to predict ultimate drip loss, color, tenderness and intramuscular fat (IMF) of pork. Barlocco and others (2006) used NIR spectroscopy to predict moisture, IMF and Warner-Bratzler shear force (WBSF) in pork samples. Similarly, Ortiz-Somovilla and others (2007) used NIR spectroscopy to predict fat, moisture and protein in minced mixtures for pork sausages. Prieto and others (2008) successfully employed NIR spectroscopy to discriminate between ground beef samples from steers and young cattle based on their chemical composition. Bajwa and others (2009) used visible NIR (Vis/NIR) spectroscopy in order to predict the nutrient quality of ground beef patties. ElMasry and others (2011) used a HSI system to assess the quality of cooked turkey hams and ElMasry and others (2013) successfully used HSI to assess major constituents in beef (water, fat, and protein). Wold and others (2016) used an industrial HSI scanner for online measurement and sorting of pork trimmings based on their fat content. In a recent study, De Marchi and others (2017) used near infrared transmittance (NIT) to predict sodium content in various commercial meat products.

Studies have also been conducted in order to predict adulteration in meat. Kamruzzaman and others (2013) used HSI to detect pork adulteration in minced lamb samples. Similarly, Morsy and Sun (2013) used Vis/NIR spectroscopy to detect adulteration in minced beef. Kamruzzaman and others (2015) used a Vis/NIR HSI system to detect adulteration in fresh minced beef with chicken. Recently, Ropodi and others (2017) used multispectral imaging (MSI) to detect horse meat adulteration in minced beef. Detailed discussions of the studies conducted using HSI are not included in this section as it warrants for a separate review, the interested reader is referred to a compilation of research papers on the topic (Xiong and others 2014; Siche and others 2016). HSI systems, indeed provide many advantages with its ability to provide spatial information. However with the advancements in the area of optics and NIR spectroscopy, fiber-optic probes can provide advantages such as: noninvasive, noncontiguous and concurrent measurements which could be beneficial in an industrial environment (Cama-Moncunill and others 2016).

All studies mentioned are either at line or off line. However, the meat processing industry is interested in on/inline analysis, which eliminates the need for procuring samples from the processing line and results are simultaneously obtained without interrupting the process.

In the last decade, studies have been conducted in order to predict online meat composition and other physical, chemical and sensory attributes using NIR spectroscopy. Table 1 illustrates different studies conducted in order to evaluate the efficacy of NIR spectroscopy performing online along with attributes predicted, spectroscopy system employed, modelling approach, and model performance summary.

Online meat analysis

This section discusses the various studies aimed at illustrating the online prediction ability of NIR spectroscopy for meat composition and quality attributes in a chronological order.

Isaksson and others (1996) conducted a study to evaluate the efficiency of a NIR spectrophotometer based on rotating filter wheels to predict the chemical composition of ground beef directly at the outlet of a meat grinder. Beef was ground through 4 different plates with hole diameters of 4, 8, 9, and 13 mm. The NIR sensing head was mounted at the outlet of the grinder. Five wavelength filters were selected to cover C-H (1728 nm) and O-H (1441 and 1510 nm) band overtones related to fat and moisture, respectively. 1655 and 1810 nm filters were selected as references with low absorbance in homogenized beef. Good predictions were obtained with 4 and 8 mm diameter grinder plates and acceptable results were obtained with 9 mm. It was concluded that sampling error contributed the most to the RMSECV (root mean square error of cross validation) due to the restricted exposure of the sample to the NIR probe and the heterogeneity of ground beef samples. Togersen and others (1999) conducted a study to predict

Table 1–A summary overview of the on/inline application of NIR spectroscopy for determining various chemical, physical and sensory attributes of meat and meat products

Product	Attribute	system	Modelling approach	Mode of NIR measurement	Stand-off distance	Spot size (diameter)	Performance summary	Reference
Ground beef	Fat, moisture and protein	Filter wheel based NIR spectrophotometer	Multivariate Linear regression was used as calibration method. Leave-one out cross-validation technique was used for validating the models.	Reflectance	200 to 300 mm	40 mm	$RMSECV_{fat} = 0.73\text{-}1.50$ $RMSECV_{moisture} = 0.75\text{-}1.33$ $RMSECV_{protein} = 0.23\text{-}0.32$	Isaksson and others (1996)
Ground beef and pork	Fat, moisture and protein	Filter wheel based NIR spectrophotometer	Multivariate Linear regression was used as calibration method. Validation was done by either full cross-validation of the calibration set or by bias corrected prediction of the test set.	Reflectance	250 mm	40 mm	$RMSECV_{fat} = 1.40\text{-}1.48$, $r = 0.87\text{-}0.98$ $SEP_{fat} = 0.82\text{-}1.49$, $r = 0.94\text{-}0.98$ $RMSECV_{moisture} = 1.09\text{-}1.25$, $r = 0.84\text{-}0.93$ $SEP_{moisture} = 1.03\text{-}1.33$, $r = 0.92\text{-}0.96$ $RMSECV_{protein} = 0.56\text{-}0.71$, $r = 0.62\text{-}0.78$ $SEP_{protein} = 0.35\text{-}0.70$, $r = 0.68\text{-}0.90$	Togersen and others (1999)
Ground frozen beef	Fat	Vis/NIR spectrophotometer	PLSR were conducted and the calibration models were validated by 2-sample-out cross validation method	Reflectance	122 mm	100 mm	$PRESS_{50\%} = 857$ $SECV_{50\%} = 1.68$, $R^2 = 0.96$ $PRESS_{50\%} = 501$ $SEP_{50\%} = 2.28$, $R^2 = 0.93$ $PRESS_{15\%} = 255$ $SECV_{15\%} = 1.00$, $R^2 = 0.96$ $PRESS_{15\%} = 398$ $SEP_{15\%} = 2.15$, $R^2 = 0.83$	Anderson and Walker (2003)
Semi-frozen ground beef	Fat, moisture and protein	Filter wheel based NIR spectrophotometer	ANOVA, PCA and PLS were conducted and the calibration models were validated by full cross validation method.	Reflectance	250 mm	40 mm	$RMSECV_{fat} = 0.48\text{-}1.11$, $r = 0.96\text{-}0.99$ $RMSECV_{moisture} = 0.43\text{-}0.97$, $r = 0.95\text{-}0.99$ $RMSECV_{protein} = 0.40\text{-}0.47$, $r = 0.60\text{-}0.77$	Togersen and others (2003)
Cooked beef	Tenderness	NIR spectrophotometer	PLSR were conducted for development of calibration models and validation.	Reflectance	Contact probe	NA	Not reported	Rust and others (2008)

(*Continued*)

Table 1–Continued.

Product	Attribute	system	Modelling approach	Mode of NIR measurement	Stand-off distance	Spot size (diameter)	Performance summary	Reference
Beef carcass (muscle)	Color, cooking loss, sensory: tenderness, juiciness, flavor, abnormal flavor and overall liking	Vis/NIR spectrophotometer	Mahalanobis distance and T-static were used in order to eliminate outliers. PLSR was performed to build and validate calibration models.	Reflectance	Not given	63.5 mm	$SEC_{color} = 0.52\text{-}0.88$, $R^2 = 0.86\text{-}0.91$ $SECV_{color} = 0.69\text{-}0.96$, $R^2 = 0.76\text{-}0.84$ $RPD_{color} = 2.02\text{-}2.48$ $SEC_{cooking\ loss} = 2.13$, $R^2 = 0.35$ $SECV_{cooking\ loss} = 2.35$, $R^2 = 0.23$ $RPD_{cooking\ loss} = 1.14$ $SEC_{texture} = 11.12\text{-}46.49$, $R^2 = 0.31\text{-}0.54$ $SECV_{texture} = 12.70\text{-}55.76$, $R^2 = 0.21\text{-}0.31$ $RPD_{texture} = 1.11\text{-}1.25$ $SEC_{sensory} = 0.34\text{-}0.56$, $R^2 = 0.21\text{-}0.59$ $SECV_{sensory} = 0.37\text{-}0.60$, $R^2 = 0.13\text{-}0.40$ $RPD_{sensory} = 1.07\text{-}1.28$	Prieto and others (2009)
Pork slices	Fat, moisture, protein, pH and shear force	Vis/NIR spectrophotometer	Wavelet transform was used in order to de-noise the spectra followed by PLSR analysis.	Reflectance	50 mm	15 mm	$RMSEC_{fat} = 0.07$, $R^2 = 0.85$ $RMSECV_{fat} = 0.09$, $R^2 = 0.77$ $RMSEC_{moisture} = 0.76$, $R^2 = 0.83$ $RMSECV_{moisture} = 0.78$, $R^2 = 0.79$ $RMSEC_{protein} = 0.47$, $R^2 = 0.82$ $RMSECV_{protein} = 0.41$, $R^2 = 0.76$ $RMSEC_{pH} = 0.09$, $R^2 = 0.87$ $RMSECV_{pH} = 0.10$, $R^2 = 0.82$ $RMSEC_{shear\ force} = 0.23$, $R^2 = 0.72$ $RMSECV_{shear\ force} = 0.36$, $R^2 = 0.28$ *values are shown for MSC combined with the first derivative preprocessed data	Liao and others (2010)
Beef carcass (LD muscle)	Glycogen and ultimate pH (pH_u)	NIR spectrophotometer with diode array detector	PCA was used in order to determine the most representative spectra. PLS models were fitted to determine pre-rigor glycogen concentration and predict pH_u followed by GPLS models which estimated the probability of the muscle to attain normal pH_u.	Reflectance	Not given	Not given	Absorbance $MSEP_{glycogen} = 7.75$, $R^2 = 0.22$ $MSEP_{pHu} = 0.13$, $R^2 = 0.18$ Reflectance $MSEP_{glycogen} = 7.75$, $R^2 = 0.23$ $MSEP_{pHu} = 0.13$, $R^2 = 0.18$	Lomiwes and others (2010)

(*Continued*)

Table 1–Continued.

Product	Attribute	system	Modelling approach	Mode of NIR measurement	Stand-off distance	Spot size (diameter)	Performance summary	Reference
Pork (LD muscle)	pH	Vis/NIR spectrophotometer	Discrete wavelet transform (DWT) was applied (Daubechies wavelet with 6 decomposition levels (db6–6) in order to de-noise the spectra followed by PLSR analysis.	Reflectance	50 mm	15 mm	RMSEC = 0.05-0.10, r = 0.91-0.98 RMSECV = 0.13-0.14 RMSEP = 0.12-0.14, r = 0.86-0.91 RPD = 1.73-1.80	Liao and others (2012)
Beef carcass	pH, color, cooking loss and Wraner-Bratzler shear force (WBSF)	Vis/NIR spectrophotometer	Mahalanobis distance was applied in order to eliminate outliers in the spectra, followed by PLSR analysis.	Reflectance	Contact probe	NA	Trial 1 (during chilling) $SECV_{pH} = 0.04$, $R^2 = 0.52$ $RER_{pH} = 7.17$, $RPD_{pH} = 1.52$ $SECV_{color} = 0.96\text{-}3.28$, $R^2 = 0.23\text{-}0.58$ $RER_{color} = 5.66\text{-}8.82$, $RPD_{color} = 1.18\text{-}1.65$ $SECV_{cooking\ loss} = 1.79$, $R^2 = 0.31$ $RER_{cooking\ loss} = 5.76$, $RPD_{cooking\ loss} = 1.21$ $SECV_{WBSF} = 6.51$, $R^2 = 0.13$ $RER_{WBSF} = 4.38$, $RPD_{WBSF} = 1.07$ Trial 2 (after chilling) $SECV_{pH} = 0.04$, $R^2 = 0.06$ $RER_{pH} = 6.10$, $RPD_{pH} = 1.08$ $SECV_{color} = 1.25\text{-}2.82$, $R^2 = 0.17\text{-}0.53$ $RER_{color} = 5.47\text{-}7.36$, $RPD_{color} = 1.09\text{-}1.44$ $SECV_{cooking\ loss} = 1.47$, $R^2 = 0.01$ $RER_{cooking\ loss} = 5.91$, $RPD_{cooking\ loss} = 1.05$ $SECV_{WBSF} = 6.98$, $R^2 = 0.08$ $RER_{WBSF} = 5.02$, $RPD_{WBSF} = 1.02$	De Marchi (2013)
Beef carcass	Ultimate pH (pH_u)	Vis/NIR spectrophotometer	PLS analysis was conducted in order to predict the nominal pH_u value.	Reflectance	10 mm	15 mm	$RMSE_{All} = 0.26\text{-}0.28$, $R^2 = 0.38\text{-}0.39$ $RMSE_{nonbulls} = 0.20\text{-}0.22$, $R^2 = 0.36\text{-}0.48$ $RMSE_{bulls} = 0.32\text{-}0.40$, $R^2 = 0.27\text{-}0.35$	Reis and Rosenvold (2014)

(*Continued*)

Table 1–Continued.

Product	Attribute	system	Modelling approach	Mode of NIR measurement	Stand-off distance	Spot size (diameter)	Performance summary	Reference
Minced beef	Fat, moisture, protein and ash	Multipoint NIR spectrophotometer with collimators	PLSR was performed to build and validate calibration models	Reflectance	10, 25 and 40 mm	Not mentioned	$RMSECV_{fat} = 3.50\text{-}6.54$, $R^2_{cv} = 0.95\text{-}0.99$, $RMSEP_{fat} = 2.79\text{-}5.67$, $R^2_p = 0.95\text{-}0.99$ $RMSECV_{moisture} = 2.25\text{-}4.49$, $R^2_{cv} = 0.96\text{-}0.99$, $RMSEP_{moisture} = 2.75\text{-}4.62$, $R^2_p = 0.94\text{-}0.98$ $RMSECV_{protein} = 1.29\text{-}2.19$, $R^2_{cv} = 0.91\text{-}0.97$, $RMSEP_{protein} = 1.56\text{-}2.28$, $R^2_p = 0.90\text{-}0.95$ $RMSECV_{ash} = 0.03\text{-}0.06$, $R^2_{cv} = 0.96\text{-}0.99$, $RMSEP_{ash} = 0.03\text{-}0.06$, $R^2_p = 0.95\text{-}0.99$	Dixit and others (2016b)
Minced beef	Fat, moisture, protein and ash	Multipoint NIR spectrophotometer with an integrated beam-splitter and collimators	PLSR was performed to build and validate calibration models	Reflectance	10, 15 and 40 mm	Not mentioned	$SECV_{fat} = 1.94$, $R^2_{cv} = 0.99$, $SEP_{fat} = 6.75\text{-}11.40$, $R^2_p = 0.77\text{-}0.94$ $SECV_{moisture} = 1.76$, $R^2_{cv} = 0.98$, $SEP_{moisture} = 4.96\text{-}9.22$, $R^2_p = 0.74\text{-}0.94$ $SECV_{protein} = 0.43$, $R^2_{cv} = 0.98$, $SEP_{protein} = 1.71\text{-}2.54$, $R^2_p = 0.85\text{-}0.91$ $SECV_{ash} = 0.04$, $R^2_{cv} = 0.96$, $SEP_{ash} = 0.11\text{-}0.19$, $R^2_p = 0.57\text{-}0.83$	Dixit and others (2016c)
Minced beef	Fat	Multipoint NIR spectrophotometer with collimators	PLSR was performed to build and validate calibration models	Reflectance	15 mm	Not mentioned	$SECV = 5.62\text{-}5.99$, $R^2_{cv} = 0.92\text{-}0.93$, $SEP = 3.05\text{-}3.97$, $R^2_p = 0.82\text{-}0.92$	Dixit and others (2016a)

fat, moisture and protein in ground beef and pork at the outlet of an industrial scale grinder. Correlation coefficients for pork samples were better in comparison to beef. This can be attributed to the different melting characteristics of the fat in pork and beef, which result in more distinct particles of beef fat than of pork fat at low temperature. This study also reveals that sampling error is the major contributor to the calibration and prediction errors. Finally, the researchers report on the development of calibration models for frozen and semi-frozen ground meat with regard to the meat processing industry. The NIR system used in both of these studies was based on a filter wheel arrangement, where proper alignment and speed of rotation are crucial in order to allow sufficient acquisition time for the spectra. Moreover, the low speed of the filter wheel (20 Hz) may not be suitable for online monitoring of faster operations such as meat grading on a conveyor belt.

Anderson and Walker (2003) employed Vis/NIR spectroscopy in order to conduct online measurements of fat content in ground beef using a conveyor system. The Vis/NIR system consisted of a diode array which analyzed the reflected light from the sample and simultaneously recorded the amount of light energy reaching the sensors, obtaining a spectral measurement every 1/30th of a second. The system does not have any moving parts, which makes it suitable for processing applications. Beef pieces were made sufficiently small using a hydroflaker before they were fed to the meat grinder. A molding head was used so that a consistent amount of ground beef was exposed to the spectrophotometer. Overall the results showed good feasibility of the system for online analysis of beef. This study illustrates a better NIR setup for online monitoring as indicated by the absence of non-moving parts and a faster spectral acquisition time. However, the system was not designed to handle situations where the effective path length rapidly changes owing to nonuniform sample surfaces. In a recent study, Dixit and others (2016c) used a NIR spectrophotometer with an integrated beam-splitter to overcome these effects. It could be possible to enhance the online monitoring ability of the Vis/NIR system illustrated by Anderson and Walker (2003) with the use of an integrated beam-splitter.

Togersen and others (2003) used NIR spectroscopy to predict the chemical composition of semi-frozen ground beef at the outlet of an industrial scale meat grinder. The study analyzed the effect of temperature from liquid water to ice on the NIR spectra. An increase in the temperature of water from 30 to 60 °C was observed to shift the absorption band between 1400 and 1500 nm toward shorter wavelengths (Iwamoto and others 1987). Fornes and Chaussidon (1978) discovered that liquid water and ice produced distinct isosbestic points at 1957 and 2008 nm, respectively. However, due to the limited penetration of NIR radiation it only experienced surface characteristics and did not encounter any effect due to the temperature gradient between the surface and the core. Therefore, the study suggests the requirement for more robust calibration models for industrial applications. This study was more focused on the deviations occurring in the spectral features due to a change in the temperature of water. The NIR setup was similar to the system illustrated in the study conducted by Togersen and others (1999) and hence did not contribute to the advancement of online NIR monitoring of meat.

Rust and others (2008) employed NIR spectroscopy to predict the tenderness of 15-d aged, cooked beef. Slice-shear force of beef rib eye rolls was measured using a WBSF and used as reference values for tenderness. The spectrophotometer was handheld with a fiber-optic contact probe in the wavelength range of 400 to 2500 nm. The study indicated that tough meat absorbed more light than tender meat. A low correlation coefficient between the observed and predicted values indicated low accuracy of the system. However, the system illustrated potential to sort carcasses into different tenderness categories. Prieto and others (2009) performed online Vis/NIR spectroscopy to predict chemical, physical and sensory characteristics of beef in an abattoir. Vis/NIR spectra were acquired with a 63.5 mm active area scanning head from *musculus longissimus thoracis* (MLT) removed from vacuum packed carcasses (steers and heifers). The muscle area was scanned by moving and rotating the scanning head, reducing sampling error by giving a better representation of the sample. Color, cooking loss, sensory analysis and Slice and Volodkevitch shear force were measured. Results showed high predictions for color measurements, however, in the infrared region, the longer wavelengths were less analytically useful, which could be attributed to high absorbance and short penetration path-length (Shackelford and others 2004). Low predictions were observed for cooking loss, which were explained by sample heterogeneity and low spectral variation such as temperature during spectral acquisition. Low predictions were observed for both shear force tests which can be partially related to the difference between the samples presented to the Vis/NIR instrument (48 h postmortem) as opposed to the reference methods used (10 and 14-d aged). Fair predictions were observed for flavor as a sensory characteristic. It should be noted that changes in fatty acids gives rise to variation in flavor. Fatty acid absorption peaks between 1000 and 1400 nm, related to C-H molecular bond gave the highest correlation with the flavor characteristic. The study shows that Vis/NIR spectroscopy was able to predict color and had good correlation with the sensory characteristics, both of which are important attributes with regard to consumer perception. Both studies used a handheld NIR system which provides the advantage of portability as well as spot checks during an ongoing process. However, the handheld system could not be employed for continuous online monitoring.

Liao and others (2010) used Vis/NIR spectroscopy to predict quality traits (IMF, protein, moisture, pH and shear force value) of fresh pork. Fresh pork slices from musculus longissimus dorsi (MLD) were scanned over a moving conveyor belt system. An optoelectronic sensor was employed to trigger the spectrometer in order to collect the spectrum. When the sample was transported into the FOV (field of view), an electrical signal was sent to the spectrometer and the reflectance spectrum of the sample was collected. It should be noted that slices were required to be flat in order to avoid baseline shifts occurring due to bed-depth variations. Absorption bands between 530 and 560 nm were observed, both related to the myoglobin and oxymyoglobin content, proving the feasibility of Vis/NIR spectroscopy for scanning pork muscle. The best predictions were observed for pH. Reasonable predictions were observed for IMF, moisture and protein. Unfortunately, poor predictions were observed for shear force values, which could be related to significant variation in the values obtained from the 4 cores taken from the sample. Heterogeneity of the muscle and its fiber arrangements and also the softness of the cores which is easily deformed were reported as the reason for the inconsistency of shear force values. The use of an optoelectronic sensor enhanced the process automaticity, which along with a low integration time of 8 ms illustrated great potential for online monitoring. However, similar to the setup used by Anderson and Walker (2003), the system was not designed to handle the effects due to rapid path length changes.

Lomiwes and others (2010) used NIR spectroscopy to determine glycogen and predict ultimate pH (pH_u) of prerigor beef MLD at a carcass grading station. NIR spectra of the freshly cut MLD from the carcasses were collected with a diode array spectrophotometer. Crushed frozen muscle samples were used for determining the prerigor glycogen and the pH_u was determined with a pH meter using a muscle slurry which provided reference values. It was observed that pH_u had significant dependence on animal class. pH_u depends on glycogen and pH at approximately 45 min post mortem (pH_{45}), bulls have much lower concentration of prerigor glycogen. Moreover, mean pH_{45} was found to be much lower in steers than bulls and cows which resulted in bulls having higher mean pH_u. Significantly different covariation was observed between pH_u and glycogen for bulls in comparison to steers and cows. Poor results were obtained in order to classify animals as per their $pH_{u.}$ Qualitative models correctly categorized 42% of high pH_u samples which were developed to categorize each muscle according to their pH_u. Optimum qualitative and quantitative models showed low correlation between predicted values and reference measurements. Results suggested that predictive models for individual animal classes may be more accurate for glycogen and muscle pH_u predictions. However, this was not investigated due to the restricted number of animals in each class. The study investigated a novel approach for online quantification of glycogen and pHu prediction of prerigor beef MLD, useful in order to detect beef eating quality. However, the models performed poorly and required more experiments. The study did not discuss the NIR setup in detail, hence conclusions regarding the system configurations could not be derived.

Liao and others (2012) used Vis/NIR reflectance spectroscopy to predict pH in fresh pork online with wavelet de-noising. MLD samples from pig carcasses were used. A spectrometer equipped with a fast response CCD (charge coupled device) detector was installed over a conveyor belt system (0.25 m/s), acquiring the reflectance spectra of the sample when it entered the FOV using an optoelectronic sensor. Reference values for pH (5.03 to 6.14) were obtained using a pH meter. Since the spectra had a low signal-to-noise ratio, signal de-noising was performed using discrete wavelet transform (DWT). In order to de-noise the spectra 2 threshold strategies (hard and soft) were used. Results showed that a smoother spectra was obtained with soft thresholding. It was verified with the results that Vis/NIR spectroscopy offers the potential to predict the pH value of fresh pork online and the use of DWT (variable selection) could provide a simpler and cost-effective calibration model. The experimental procedure conducted and NIR setup in this study were similar to Liao and others (2010). The main feature of this study was the use of DWT to de-noise the scanned spectra as online operation enlarges the noise component. A detailed discussion about DWT can be found elsewhere (Pasti and others 1999).

De Marchi (2013) used Vis/NIR reflectance spectroscopy to predict beef quality traits such as pH, color indexes, cooking loss and WBSF. Two trials were conducted using cattle carcasses as samples. In the first trial, carcasses of bulls and heifers were used while in the second trial cattle carcasses from different breeds were used (Charolais, Limousin, and Irish crosses). Vis/NIR measurements were taken after 4 to 6 h postmortem for trial 1 and 14 to 16 h postmortem for trial 2. The spectrum was collected within the abattoir by placing the scanning head over the surface of the exposed *gracilis* muscle. Laboratory analysis were conducted in order to obtain reference values for pH, color indexes, cooking loss and shear force; pH was measured using an intact MLT. Color indexes were measured on MLT after 1 h of air exposure with a Minolta colorimeter. Cooking loss was determined by the difference in sample (thick MLT) weight before and after cooking. Shear force was determined using a TA-HDi Texture Analyzer with a Warner–Bratzler shear attachment. Results showed fairly good predictions for color, cooking loss, and pH of MLT whereas poor predictions were reported for WBSF. Limitations of the study were related to the standardization of the spectra collection and low accuracies of the calibration models. The study suggested the importance of proper scheduling and positioning for spectra collection which is difficult due to heterogeneity within the animals and slaughtering conditions. However, it may be possible to improve the calibration equation using a larger dataset. Reis and Rosenvold (2014) used NIR spectroscopy for early online classification of beef carcasses based on pH_u. Carcasses included were those from cows, bulls, steers and heifers. Reflectance spectra were collected using a Vis/NIR spectrophotometer which was located at the grading station. Reference values for glycogen were obtained using a commercial system based on enzymatic conversion of glycogen to glucose. Color measurements were performed using a Hunter Lab system. Fresh cut surface of meat was bloomed for 30 min before taking color measurements. The best correlations were obtained between pH_u and color parameters: a*-value and b*-value. Calibration models showed a limited ability to predict the nominal pH_u value. The best approach to evaluate pH_u was to use 2 separate models for bulls and non-bulls. Overall results showed that NIR spectroscopy has the potential to replace wet chemistry analysis of pH_u for prime animals (steers + heifers). Both studies involved the use of a hand-operated NIR system which was appropriate for abattoirs. However, both designs did not show much potential for online monitoring in a processing plant which required constant monitoring.

Dixit and others (2016b) used a NIR spectrophotometer, based on a Fabry-Perot interferometer with 4-measurement channels attached to 4 collimating lenses to estimate fat, moisture, protein and ash content of minced beef samples at different stand-off distances (10, 25, and 40 mm). Measurements were conducted in static and 2 different rotating motion conditions; 100 rpm (0.074 m/s) and 210 rpm (0.156 m/s) by placing the collimator fitted probes perpendicular to the sample. Motion conditions were employed to simulate conditions of a meat processing plant. Reference values were obtained by performing proximate analysis. Data obtained was preprocessed using standard normal variate (SNV) transformation and Savitzky–Golay smoothing in order to enhance signal-to-noise ratio followed by partial least squares regression (PLSR) modelling of each compositional attribute. Results showed good prediction accuracy for each attribute in all combinations of stand-off and motion conditions. Best predictions were obtained at a stand-off distance of 10 mm for a speed of 210 rpm, as a greater surface area is analyzed in motion conditions. The portability of the device along with the ability to perform measurements in motion conditions illustrated great potential as an inline monitoring tool for the meat processing industry. In a later study, Dixit and others (2016c) used a multipoint NIR spectrophotometer system incorporating a beam-splitter, combined with collimated light to perform online analysis of minced beef composition. The beam-splitter performed baseline correction in cases of sudden effective path length changes by the adaptive adjustment of the spectra, which can often occur in a meat processing plant. Additionally, the study also aimed at demonstrating the ability of the multipoint NIR spectrophotometer to provide spatial information. Sample preparation was performed following the methodology described by Dixit and others (2016b). A separate batch was prepared in the form of a square grid (8 × 6 array) consisting a total of 48 samples. The grid was prepared to illustrate 2 key features of the device presented; (a) automatic baseline correction and (b) generation of spatial information. The 4 collimating probes were arranged in a straight line, where each probe was exposed to a different sample and distance (10, 15, and 40 mm) depending on its position along the grid. Measurements were conducted in static and vibrating motion conditions (360 rpm). In order to illustrate the automatic baseline correction feature, the sample grid was manually moved during each scan towards the same sample replicate at a different stand-off distance to produce a sudden shock due to a rapid change in sample presentation. Results showed that the NIR spectrophotometer spatially predicted the chemical composition of minced beef samples at different path lengths with good accuracy, both with and without baseline correction. Overall it was concluded that the addition of collimators and the use of a beam-splitter made this spectrophotometer highly suitable for a typical real-scenario in an industrial environment. In another study, Dixit and others (2016a) used a multipoint NIR spectrophotometer system, combined with a flexible collimator–probe arrangement for real-time analysis of beef fat content. The main objective of the study was to demonstrate the flexibility and independency of 4 collimator-fitted NIR probes, that could be placed at distances of up to 4 m apart, to assess fat content in minced beef concurrently under both static and motion conditions. The collimator-fitted probes were placed at a stand-off distance of 15 mm and measurements were taken concurrently under static and rotational motion conditions in a random order; 100 rpm (0.15 m/s) and 210 rpm (0.31 m/s). Two probes were positioned to scan samples in static condition while the other 2 collimating probes were positioned to scan samples in rotational motion. Fat content was determined with a Soxhlet apparatus following a standard method of the AOAC (2000). Results showed good fat predictions both in static as well as in motion conditions. In order to illustrate the collimator probe independency, 2 samples with different fat percentages were scanned concurrently in static and motion conditions. Spectral features obtained clearly differentiated samples based on their fat related absorption peaks at 1754 and 1768 nm. Overall, it was concluded that the multipoint NIR spectroscopy system holds great potential for performing in-line monitoring of food products at various junctions in a meat processing plant.

The last 3 studies illustrate the different features of a novel NIR system including; (a) multipoint analysis for better sample representation as well as spatial features, (b) high stand-off distances with collimators minimizing sample interference, (c) automatic baseline correction with beam-splitter for overcoming shifts due to sudden path length changes, and (d) probe independency and flexibility for analyzing different samples concurrently and in different motion conditions.

The studies discussed in this section illustrate various applications of NIR spectroscopy for online meat analysis which provides certain advantages to the meat processing industry: (a) real-time quality monitoring, (b) reduction in number of chemical tests, (c) lower possibility of hazards, and (d) overall cost reduction with better product quality. However, the industrial application of these novel NIR systems require further work involving the development of robust calibration models by using large sample sets as well as industrial trials with various meat products. Moreover, it is also important to study and take into account the effects due to different external factors such as instrumental variations (instrument temperature, wavelength shifts, illumination source, stability, and so on) and sample variations (sample temperature, sample homogeneity, height differences between probes and sample, and so on). Overall significant technology developments have occurred over this period to the point where large-scale industrial trials over extended periods are warranted. With this in mind high stand-off distances, automatic baseline correction and multipoint systems are recommended.

Role of Chemometrics

Chemometrics is a discipline that deals with the use of computer and information technologies to solve chemical problems (Iwaniak and others 2015). NIR spectra are greatly influenced by nonlinearities introduced by light scattering effects such as Mie scattering and optical scattering. Both baseline shifts and nonlinearities occur due to a considerable difference between the size of the wavelength in the NIR region and the particle size of the sample. For example, in solid samples, a loss in the amount of light (diffused reflected) getting back to the detector could give rise to baseline shifts (multiplicative effects), generally influenced by differences in the effective path length. In the case of NIR-reflectance for liquid samples or samples with shiny surfaces, a phenomenon called specular reflectance (mirror-like reflections) takes place, which prevents obtaining valuable information from the samples.

Preprocessing techniques

This section concentrates on the most-common preprocessing techniques which have been used (Table 1) in order to minimize the multiplicative effects and other nonlinearities caused by the scattering phenomenon. These techniques can be divided into 2 categories; scattering correction methods and spectral derivatives.

MSC (multiplicative scattering correction), EMSC (extended multiplicative scattering correction), and SNV are the most frequently used scattering correction techniques. MSC is probably the most widely used technique for preprocessing of the NIR spectra. It removes undesired scatter effects from the data matrix, involving 2 steps: (a) estimation of the correlation coefficient and (b) correction of the recorded spectrum. MSC was the most common preprocessing technique used among various studies conducted by Wold and others (2006), Rust and others (2008), Prieto and others (2009), and De Marchi (2013) for online meat analysis. EMSC is the extended version of MSC, which normally involves the fitting of a second order polynomial to the reference spectrum, baseline fitting on the wavelength axis and the use of theoretical information from the spectra of interest (Thennadil and Martin 2005; Rinnan and others 2009). Reis and Rosenvold (2014) used EMSC as a preprocessing technique for spectra acquired on beef carcasses. SNV is the second most popular preprocessing technique after MSC. Its basic format is similar to that of MSC except that a common reference signal is not required in the case of SNV. The relation between SNV and MSC can be represented as:

$$x_{MSC} \approx x_{SNV} \,.\, \overline{S_x} + \overline{\overline{X}} \tag{1}$$

where $\overline{S_x}$ is the average standard deviation of all spectra, and $\overline{\overline{X}}$ is the grand mean overall spectra, both obtained from the raw spectra (Dhanoa and others 1994).

In different studies conducted by Wold and others (2006, 2011), De Marchi (2013), Gou and others (2013), Dixit and others (2016a, 2016b, 2016c) for online prediction of different chemical, physical and sensory characteristics of meat, SNV was the common preprocessing technique used for removing noise from the spectra. It could be inferred that MSC and SNV are the same for most practical applications.

Spectral derivatives on the other hand, have the capability to remove both additive and multiplicative effects. Savtizky–Golay (SG) derivative is probably the most popular method for numerical derivation of a vector that includes a smoothing step (Madden 1978). Smoothing is required in order to reduce the signal-to-noise ratio (Cen and He 2007). A detailed discussion about preprocessing techniques can be found elsewhere (Rinnan and others 2009; Bakeev 2010).

Modeling approach in various studies

Once the data is preprocessed, it is then subjected to different multivariate statistical techniques in order to build models and validate them. Table 1 illustrates the different modelling approaches adopted by various studies related to on/inline NIR meat analysis. Building a reliable calibration model is of utmost importance for quantitative and qualitative analysis of meat (Cen and He 2007). This section gives a general overview of the most commonly employed modelling approaches. Linear regression is the simplest predictive modelling technique that relates a single independent variable to a single dependent variable (MacGregor and Bruwer 2008). Multiple linear regression (MLR) is an extension involving the use of several independent variables, often required for NIR spectroscopy applications due to the inability to find a suitable single response variable (Bakeev 2010).

Spectroscopic data obtained from NIR analysis often contains a large number of strongly correlated variables in the range of hundreds to thousands, presenting mathematical and computational issues when working. Hence, data compression is required in order to reduce the data into a representation of fewer variables, representing most of the information. Principal component analysis (PCA) is the most common data reduction method, which transforms the original data matrix into a simpler representation that uses a significantly reduced number of compressed variables called principal components (PCs). Each PC can be explained as a linear combination of the original variables and the importance of each of these variables is defined by the loadings. It is a technique which identifies patterns in the data and show them in such a way that similarities and differences can be observed (Hu and others 2015). PCA was employed in the studies conducted by Togersen and others (2003) and Lomiwes and others (2010) for online analysis of beef.

Modelling approaches can be divided into 2 categories: (a) multivariate calibration and (b) classification.

Multivariate calibration. Multivariate calibration approach uses preprocessed NIR data and reference values from chemical analysis, for example, proximate analysis, pH measurements, and so on to build calibration models which can predict and quantify values from a similar NIR data set (validation set). MLR, principal component regression (PCR) and PLSR are the most common multivariate calibration methods used in NIR analysis of meat. Table 2 shows the equations for different quantitative models along with the meaning of the terms involved. MLR relates concentration as a function of absorbance, which involves information of the concentrations of the target analytes along with other components that contribute to the overall signal (Blanco and Villarroya 2002). MLR was used as a calibration method in the studies conducted by Isaksson and others (1996) and Togersen and others (1999) for online analysis of ground meat. Similar to MLR, PCR is also an inverse calibration method and an extension of PCA, where PCs obtained from PCA are used as variables in a MLR model. Firstly PCA is done on the calibration data, generating PCA scores and loadings followed by MLR (Gemperline 2006). Cozzolino and Murray (2004) utilized PCR to identify and authenticate minced samples of beef, lamb, pork and chicken meat. PLSR utilizes the exact same mathematical model as PCR with the exception that in PCR, the data compression is performed using only spectral information, while PLS employs spectral and concentration data (Hemmateenejad and others 2007). The compressed variables obtained in PLSR are referred to as latent variables (LVs). PLSR mathematically correlates the spectral data to a matrix of the property of interest (chemical or physical attributes) concurrently with all the other significant spectral factors that disturb the spectrum (ElMasry and others 2012). The procedure has 2 steps, the first is the calibration and the second is the prediction that tests the calibration model (Meza-Márquez and others 2010). PLSR was the common modelling approach used in the studies conducted by Anderson and Walker (2003); Rust and others (2008); Prieto and others (2009); Liao and others (2010); Liao and others (2012), De Marchi (2013), Dixit and others (2016b), Dixit and others (2016c) and Dixit and others (2016a).

However, to perform multivariate calibration in situations where the relationship between x and y variables are highly nonlinear; techniques such as artificial neural network (ANN) and support vector machine (SVM) have been proved to be useful (Wu and others 1996; Li and He 2008). ANN is a computing system made up of a number of simple, highly interconnected processing elements, which simulate the parallel processing of a human brain to convert input variables into meaningful outputs. ANN's model structure is expressed by a map and the model parameters are determined by a searching algorithm (Blanco and others 2000; Bakeev 2010). Back propagation neural network (BPNN) is one of the most common neural network technique used for nonlinear modelling of NIR data. BPNN provides the advantages such as quick response and high learning accuracy. Network architecture, network parameters, and the problem complexity defines the superiority of a network's function approach. Significance of results heavily rely on the selection of appropriate network architecture and parameters. BPNN comprises of an input layer, hidden layer, and output layer. BPNN parameters include: the number of hidden layers, number of hidden neurons, learning rate, momentum, and so on which have significant impacts on the performance of the neural-network (Chen and Hsu 2007; Chen and others 2010). Liu and others (2010) used PLSR and PCA-BPNN for nondestructive measurement of soluble solid content of navel orange fruit by (VIS/NIR) spectroscopy. In another study, Liu and others (2009) performed BPNN and least squares-support vector machine (LS-SVM) combined with Vis/NIR spectroscopy to implement the fast discrimination of instant milk teas. To the best of our knowledge, studies involving the use of ANN combined with NIR spectroscopy for meat products have not been reported to date. Support Vector Machine (SVM) is another method to perform nonlinear modelling of spectral data. The following attributes of SVM makes it different from other regression techniques; (a) SVM can perform more efficient modelling of nonlinear or complex data structures by using nonlinear transform functions, called kernels, (b) model coefficients are not determined using the standard least squares minimization criterion but using a more complex criterion; and (c) a developed SVM model is expressed in terms of a series of vectors, called support vectors, rather than a single regression coefficient vector. The disadvantage of using SVM is that the regression models do not consider all calibration samples equally, but rather depends heavily on a

Table 2–Models for various quantitative modeling methods

Method	Model	Meaning of terms
Linear regression	$y = bx + b_0 1 + \mathrm{f}$	y: vector of measured independent variables, **x**: matching vector of measured dependent variables, **1**: vector of ones and **f**: vectors containing the residuals of the linear regression model.
MLR (multiple linear regression)	$y = \mathrm{bX} + \mathrm{f}$	**X**: matrix that contains responses from M (>1) different x variables and **b**: It contains M regression coefficients for each of the x variables.
PCR (principal component regression)	$y = \hat{\mathrm{T}}\,\mathrm{q} + \mathrm{f}$ $\hat{\mathrm{q}} = (\hat{\mathrm{T}}^{\mathrm{t}}\hat{\mathrm{T}})^{-1} + \hat{\mathrm{T}}^{\mathrm{t}}\mathrm{y}$	y: It contains the known values of the property of interest, $\hat{\mathrm{T}}$: PCA scores and **q**: It contains the y loadings of the PCR model. $\hat{\mathrm{q}}$: y loadings, obtained using the least squares procedure.
PLSR (partial least squares regression)	$\hat{\mathrm{b}}_{PLS} = \hat{\mathrm{W}}_{PLS}(\hat{\mathrm{P}}^{\mathrm{t}}_{PLS}\hat{\mathrm{W}}_{PLS})^{-1}\hat{\mathrm{q}}$ $\hat{y}_{p,PLS} = \hat{\mathrm{b}}_{PLS}\mathrm{X}_{\mathrm{p}}$	$\hat{\mathrm{b}}_{PLS}$: regression coefficients, $\hat{\mathrm{W}}_{PLS}$: Loading weights, $\hat{\mathrm{P}}_{PLS}$: x loadings and $\hat{\mathrm{q}}$: y loadings. $\hat{y}_{p,}$: value of unknown sample and $\hat{x}_p$: array of x values.

subset of samples that are most effective for modelling the property of interest (Thissen and others 2004; Dixon and Brereton 2009; Bakeev 2010). Studies involving the use of SVM combined with NIR spectral data for meat analysis have only been reported with HSI (Pierna and others 2004; Xiong and others 2015; Kamruzzaman and others 2016), which warrants for a separate review. The interested reader is referred to a compilation of research papers on the topic (Siche and others 2016; Xiong and others 2014).

Classification. Classification techniques are employed when it is not possible to quantify and when quantification may lead to misleading results. Classification techniques differentiate groups depending upon their quality attributes. PLS-discriminant analysis (PLS-DA), linear discriminant analysis (LDA) and soft independent modelling of class analogies (SIMCA) are commonly used classification techniques for NIR analysis of meat. PLS-DA utilizes a quantitative regression method of PLS in order to perform qualitative analysis. It involves the application of PLS algorithms followed by the determination of a discriminant threshold value for each class. PLS-DA decomposes the spectra as linear combinations of PCs, which expresses the major part of information contained in the dataset. The latent variables (LVs) are then generated from the input variables to maximize the variance between sample classes in the model (Tian and others 2014). LDA uses a space defined by a set of vectors called *linear discriminants* (LDs), which are similar to the PCs generated in PCA. It is a technique based on probabilistic classification, which searches for canonical variables with maximum separation between categories; the first canonical variable is the direction of maximum ratio between inter-class and intra-class variances (Casale and others 2015). Ropodi and others (2015) utilized PLS-DA and LDA as a multivariate technique to detect adulteration of minced beef with pork meat and vice-versa using multispectral imaging. Unlike PLS-DA and LDA, which works on a strategy to find directions in a common space that separate known classes, SIMCA works on a strategy that defines a unique space for each class, define class-specific models using their respective spaces, and then apply an unknown sample to these models in order to assess class membership (Bakeev 2010). Meza-Márquez and others (2010) utilized SIMCA for detecting adulterants in minced beef using mid-infrared spectroscopy.

Multivariate curve resolution (MCR) is a technique which attempts to impose specific constraints on the properties of the scores or loadings obtained from a PCA or PLS model, so that they can be rotated to a more physically meaningful form. MCR is focused on the determination of qualitative information and on the recovery of the response functions of the components present in unresolved mixtures, whereas multivariate calibration methods are more focused on estimation of quantitative information (Jaumot and others 2013). Multivariate curve resolution-Alternating least squares (MCR-ALS) is the most popular chemometric method used for the resolution of multiple component responses in unknown unresolved mixtures (Jaumot and others 2005). It is an iterative method that performs a bilinear decomposition of the built data matrix by means of an alternating least squares optimization (Felten and others 2015; Folch-Fortuny and others 2015). MCR-ALS is not a popular technique for meat analysis using NIR spectroscopy. However, its application as a multivariate technique in several studies using NIR systems for different products is found (Alexandrino and Poppi 2013; Colares and others 2016). Apart from the mentioned modelling approaches there are several other techniques which can be found elsewhere (Bakeev 2010).

Advancements, Challenges, and Future Possibilities

On/inline NIR analysis of meat has observed a rapid development in the last decade or so. One of the major obstacles while performing NIR analysis are low stand-off distances in the range of millimeters (Prieto and others 2015; Pullanagari and others 2015; Srivichien and others 2015). The use of direct sample illumination by a halogen light source makes it possible to use high probe stand-off distances in the range of 30 cm or more. A combined illumination and sensor unit is also available commercially which claims to work in the range of 15 to 60 cm stand-off distances (PSS-H-A03, Polytec GmbH Waldbronn, Mich., U.S.A.). However, the amount of heat energy produced by the halogen source would not be feasible on heat liable materials. Introduction of collimators is a solution to this issue that can operate up to 4 cm stand-off distances and are fitted with fiber optic probes. The light from a halogen light source travels through the fibers and finally the collimated light illuminates the sample, thus the amount of incident heat energy is far less in comparison to a direct halogen light. The use of halogen light and higher stand-off distances is also one of the reasons for better suitability of NIR spectroscopy for on/inline applications.

A major issue is the imprecise representation of sample composition of highly heterogeneous samples such as meat when using single point NIR spectroscopy. Multipoint NIR spectroscopy illustrates the potential to offer better representation of these samples. Additionally, it also provides spatial information. The use of a flexible multiprobe system illustrates the potential for conducting independent concurrent measurements (Cama-Moncunill and others 2016). Moreover, the fiber-optic probes have been reported to work approximately 30 m apart from each other (Klimkiewicz and others 2014). Hence, a single NIR system could be used to monitor different control points in a meat processing plant situated at farther distances. Figure 2 illustrates these different probe types and configurations. Among the obstacles while performing online NIR analysis are the motion artifacts (MAs) produced due

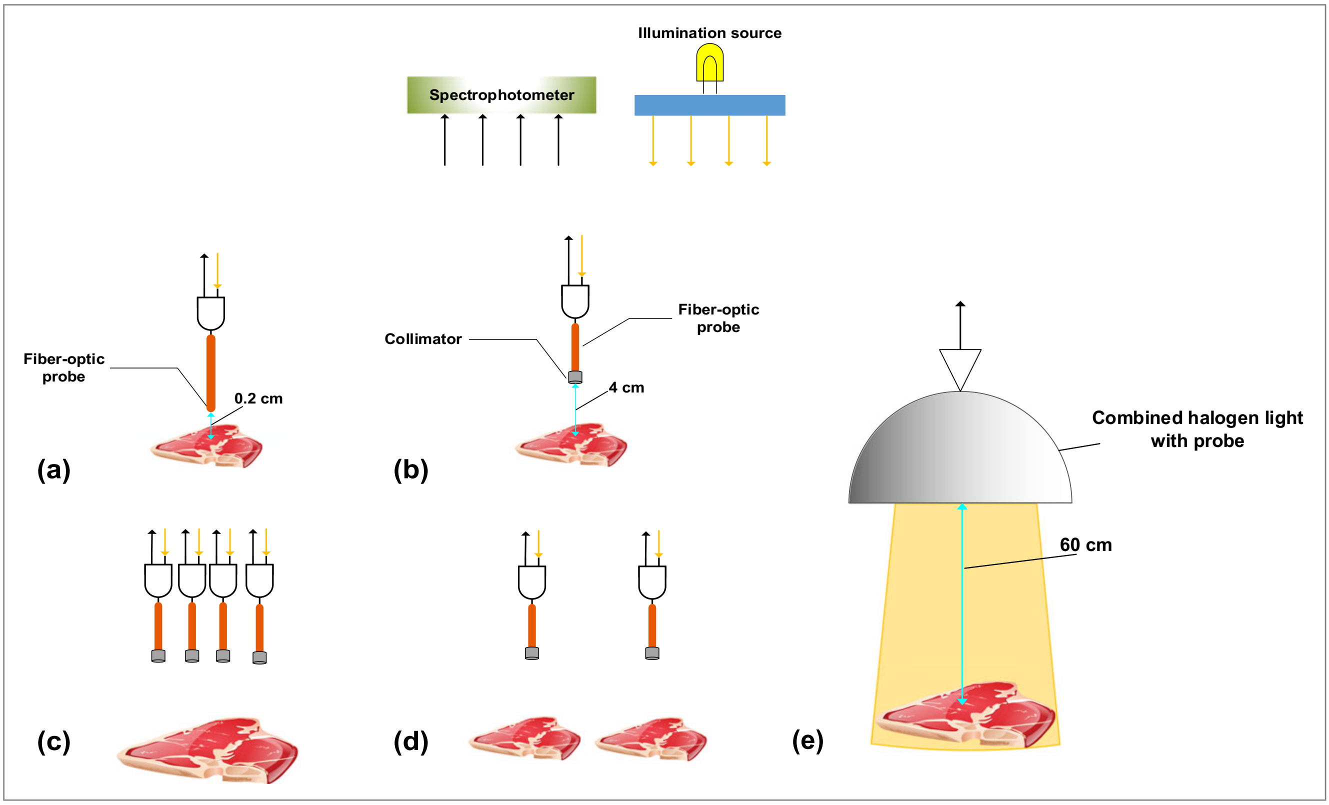

Figure 2–Probe types and configuration: (a) single point fiber-optic probe, (b) single point fiber-optic probe with collimator, (c) Multipoint fiber-optic probe with collimators, (d) Concurrent measurements using fiber-optic probes with collimators, and (e) Combined halogen light with probe. (↑ indicates connection to the spectrophotometer and ↓ indicates light approaching from the illumination source).

to vibrations, motion between probes and the sample and sudden change in effective path length. A possible solution is the use of beam-splitter with a spectrophotometer which allows to automatically overcome baseline effects (Dixit and others 2016c). Moreover, statistical algorithms such as wavelet transform and Kalman filtering could overcome these artifacts (Velardi and others 2009; Liao and others 2012).

Spectroscopic observations depends on clean observation window (cleanliness of the probe tips). If fouling occurs on the probe tip such as the sample (for example, meat emulsion) adhering onto the fiber, it will eventually lead to poor analysis. Developments in fiber design have seen the emergence of easy-clean or self-clean fibers. Commercially available Lighthouse probes (GEA, Düsseldorf, Germany) could overcome this issue as it provides in-process window cleaning and recalibration during the process and has been successfully employed in a pharmaceutical study by Marković and others (2014). Inline monitoring of drying or freezing processes for meat products could be monitored with NIR spectroscopy provided appropriately designed probes are used. Flame resistant probes (FL400, OceanOptics, Fla., U.S.A.) are commercially available in the market and can operate in the temperature range of −269 to 700 °C. All of these features demonstrate the capability of single or multiprobe NIR spectroscopy systems to conduct on/inline monitoring at various stages of meat processing in an industrial setting.

In an industrial environment, NIR measurements are sensitive to various external factors such as ambient temperature, spectrophotometer temperature, sample presentation to the NIR probes, wavelength shifts and others. Alexandrakis (2012) suggests to overcome the influence of these factors it is important to understand the sample and environment and to identify the effects of these factors on the respective spectra. Extensive experimental designs such as RSM (response surface methodology) could be utilized in order to identify and measure these influences. Chemometrics plays an important role in dealing with these issues. Several correction strategies such as optical methods, orthogonal methods and bias correction can be used in achieving robust calibration models in an industrial environment. Detailed discussion about these techniques can be found elsewhere (Zeaiter and others 2006; Roger and others 2008).

Conclusions

NIR spectroscopy has experienced massive growth as a popular and reliable analytical tool for online monitoring of meat and meat products due to a variety of reasons such as speed and its nondestructive nature High performances have been achieved in the studies aimed at predicting chemical composition of various meat and meat products using on/inline NIR spectroscopy systems. Good or reasonable predictions for sensory characteristics such as color, tenderness, and so on and also for pH have illustrated high potential for NIR spectroscopy, however advancements in the technology and design may be required to meet the desired performance under industrial conditions.

Advancements in the on/inline application of NIR spectroscopy for meat and meat products such as using high standoff distances, multipoint spectroscopy, fiber-optic probe independency and flexibility, and concurrent measurements have immensely increased the potential of the technology as a reliable inline monitoring tool for the meat industry. Moreover, the continuous developments in the fields of computer technology and chemometrics allow a high dependency on accurate reference measurements (chemical, physical and sensory analysis) to be minimized. The increasing awareness about the authenticity of meat and meat products and on-going research and advancements in the area of on/inline application of NIR spectroscopy, illustrates its great potential as a reliable quality monitoring tool for the meat processing industry.

Abbreviations

ALS	Alternating least squares
ANN	Artificial neural networks
AOAC	Association of Official Agricultural Chemists
BPNN	Back propagation neural network
CCD	Charge coupled device
DWT	Discrete wavelet transform
EMSC	Extended multiplicative scatter correction
FAO	Food and Agriculture Organization
FOV	Field of view
HSI	Hyperspectral imaging
IMF	Intra-muscular fat
LDA	Linear discriminant analysis
LV	Latent variable
MA	Motion artifacts
MCR	Multivariate curve resolution
MLD	Musculus longissimus dorsi
MLR	Multiple linear regression
MLT	Musculus longissimus thoracis
MSC	Multiplicative scatter correction
MSI	Multispectral imaging
NIR	Near-infrared
NIT	Near-Infrared transmittance
PAT	Process analytical technology
PC	Principal component
PCA	Principal components analysis
PCR	Principal components regression
PLS	Partial least squares
PLSR	Partial least squares regression
RMSECV	Root mean square error of cross validation
RMSEP	Root mean square error of prediction
SECV	Standard error of cross validation
SEP	Standard error of prediction
SG	Savitzky-Golay
SIMCA	Soft independent modeling of class analogies
SNV	Standard normal variate
SVM	Support vector machine
Vis/NIR	Visible/Near-infrared
WBSF	Warner-Bratzler shear force

Conflict of Interest

The authors declare that there are no conflicts of interest.

Acknowledgments

The authors would like to acknowledge funding from the Food Institutional Research Measure administered by the Dept. of Agriculture, Food and the Marine, Ireland (Grant agreement: 13/F/508).

Author Contributions

Dixit searched prior studies available in the literature and drafted the manuscript. Casado-Gavalda, R. Cama-Moncunill, X. Cama-Moncunill, Markiewicz-Keszycka, Cullen and Sullivan critically examined and revised the manuscript.

References

Alexandrakis D. 2012. NIRS in an industrial environment. Near Infrared Suppl. European Pharmaceutical Review 17:3–6.

Alexandrino GL, Poppi RJ. 2013. NIR imaging spectroscopy for quantification of constituents in polymers thin films loaded with paracetamol. Anal Chim Acta 765:37–44.

Anderson NM, Walker PN. 2003. Measuring fat content of ground beef stream using on-line visible/NIR spectroscopy. Trans ASAE 46: 117–24.

Bajwa SG, Kandaswamy J, Apple JK. 2009. Spectroscopic evaluation of the nutrient value of ground beef patties. J Food Engr 92:454–60.

Bakeev KA. 2010. Process analytical technology: spectroscopic tools and implementation strategies for the chemical and pharmaceutical industries West Sussex, United Kingdom: John Wiley & Sons.

Barlocco N, Vadell A, Ballesteros F, Galietta G, Cozzolino D. 2006. Predicting intramuscular fat, moisture and Warner-Bratzler shear force in pork muscle using near infrared reflectance spectroscopy. Anim Sci 82:111–16.

Blanco M, Coello J, Iturriaga H, Maspoch S, Pages J. 2000. NIR calibration in non-linear systems: different PLS approaches and artificial neural networks. Chemometr Intell Lab Syst 50:75–82.

Blanco M, Villarroya I. 2002. NIR spectroscopy: a rapid-response analytical tool. TrAC - Trends Anal Chem 21:240–50.

Cama-Moncunill R, Markiewicz-Keszycka M, Dixit Y, Cama-Moncunill X, Casado-Gavalda MP, Cullen PJ, Sullivan C. 2016. Multipoint NIR spectroscopy for gross composition analysis of powdered infant formula under various motion conditions. Talanta 154:423–30.

Casale M, Bagnasco L, Giordani P, Mariotti MG, Malaspina P. 2015. NIR spectroscopy as a tool for discriminating between lichens exposed to air pollution. Chemosphere 134:355–60.

Cen H, He Y. 2007. Theory and application of near infrared reflectance spectroscopy in determination of food quality. Trends Food Sci Technol 18:72–83.

Chen W-C, Hsu S-W. 2007. A neural-network approach for an automatic LED inspection system. Expert Syst Applicat 33:531–37.

Chen W-C, Hsu Y-Y, Hsieh L-F, Tai P-H. 2010. A systematic optimization approach for assembly sequence planning using Taguchi method, DOE, and BPNN. Expert Syst Applicat 37:716–26.

Colares CJ, Pastore TC, Coradin VT, Marques LF, Moreira AC, Alexandrino GL, Poppi RJ, Braga JW. 2016. Near infrared hyperspectral imaging and MCR-ALS applied for mapping chemical composition of the wood specie Swietenia Macrophylla King (Mahogany) at microscopic level. Microchem J 124:356–63.

Cozzolino D, Murray I. 2002. Effect of sample presentation and animal muscle species on the analysis of meat by near infrared reflectance spectroscopy. J Near Infrared Spectrosc 10:37–44.

Cozzolino D, Murray I. 2004. Identification of animal meat muscles by visible and near infrared reflectance spectroscopy. LWT - Food Sci Technol 37:447–52.

De Marchi M. 2013. On-line prediction of beef quality traits using near infrared spectroscopy. Meat Sci 94:455–60.

De Marchi M, Manuelian CL, Ton S, Manfrin D, Meneghesso M, Cassandro M, Penasa M. 2017. Prediction of sodium content in commercial processed meat products using near infrared spectroscopy. Meat Sci 125:61–5.

Dhanoa M, Lister S, Sanderson R, Barnes R. 1994. The link between multiplicative scatter correction (MSC) and standard normal variate (SNV) transformations of NIR spectra. J Near Infrared Spectrosc 2:42–47.

Dixit Y, Casado-Gavalda MP, Cama-Moncunill R, Cama-Moncunill X, Cullen PJ, Sullivan C. 2016a. Prediction of beef fat content simultaneously under static and motion conditions using near infrared spectroscopy. J Near Infrared Spectrosc 24:353–61.

Dixit Y, Casado-Gavalda MP, Cama-Moncunill R, Cama-Moncunill X, Jacoby F, Cullen PJ, Sullivan C. 2016b. Multipoint NIR spectrometry and collimated light for predicting the composition of meat samples with high standoff distances. J Food Engr 175:58–64.

Dixit Y, Casado-Gavalda MP, Cama-Moncunill R, Markiewicz-Keszycka M, Cruise P, Jacoby F, Cullen PJ, Sullivan C. 2016c. NIR spectrophotometry with integrated beam splitter as a process analytical technology for meat composition analysis. Anal Methods 8:4134–41.

Dixon SJ, Brereton RG. 2009. Comparison of performance of five common classifiers represented as boundary methods: Euclidean distance to centroids, linear discriminant analysis, quadratic discriminant analysis, learning vector quantization and support vector machines, as dependent on data structure. Chemometr Intell Lab Syst 95:1–17.

ElMasry G, Iqbal A, Sun D-W, Allen P, Ward P. 2011. Quality classification of cooked, sliced turkey hams using NIR hyperspectral imaging system. J Food Engr 103:333–44.

ElMasry G, Sun D-W, Allen P. 2012. Near-infrared hyperspectral imaging for predicting colour, pH and tenderness of fresh beef. J Food Engr 110:127–40.

ElMasry G, Sun D-W, Allen P. 2013. Chemical-free assessment and mapping of major constituents in beef using hyperspectral imaging. J Food Engr 117:235–46.

FAO. FAO's Animal Production and Health Division: Meat & Meat Products. 2016.

Felten J, Hall H, Jaumot J, Tauler R, de Juan A, Gorzsás A. 2015. Vibrational spectroscopic image analysis of biological material using multivariate curve resolution–alternating least squares (MCR-ALS). Nat Protocols 10:217–40.

Folch-Fortuny A, Tortajada M, Prats-Montalbán J, Llaneras F, Picó J, Ferrer A. 2015. MCR-ALS on metabolic networks: obtaining more meaningful pathways. Chemometr Intell Lab Syst 142:293–303.

Fornes V, Chaussidon J. 1978. An interpretation of the evolution with temperature of the $\nu 2 + \nu 3$ combination band in water. J Chem Phys 68:4667–71.

Gemperline P. 2006. Practical guide to chemometrics. Boca Raton, FL: CRC Press.

Gou P, Santos-Garces E, Hoy M, Wold JP, Liland KH, Fulladosa E. 2013. Feasibility of NIR interactance hyperspectral imaging for on-line measurement of crude composition in vacuum packed dry-cured ham slices. Meat Sci 95:250–55.

Hemmateenejad B, Akhond M, Samari F. 2007. A comparative study between PCR and PLS in simultaneous spectrophotometric determination of diphenylamine, aniline, and phenol: effect of wavelength selection. Spectrochim Acta Part A: Mol Biomol Spectrosc 67:958–65.

Hoving-Bolink A, Vedder H, Merks J, De Klein W, Reimert H, Frankhuizen R, Van den Broek W. 2005. Perspective of NIRS measurements early post mortem for prediction of pork quality. Meat Sci 69:417–23.

Hu L-Q, Yin C-L, Zeng Z-P. 2015. Detection of adulteration in acetonitrile using near infrared spectroscopy coupled with pattern recognition techniques. Spectrochim Acta Part A: Mol Biomol Spectrosc 151:34–39.

Isaksson T, Nilsen BN, Togersen G, Hammond RP, Hildrum KI. 1996. On-line, proximate analysis of ground beef directly at a meat grinder outlet. Meat Sci 43:245–53.

Iwamoto M, Uozumi J, Nishinari K. 1987. Preliminary investigation of the state of water in foods by near infrared spectroscopy. In: Proceedings of the Intl NIR/NIT Conference, Budapest, Hungary p 3–12.

Iwaniak A, Minkiewicz P, Darewicz M, Protasiewicz M, Mogut D. 2015. Chemometrics and cheminformatics in the analysis of biologically active peptides from food sources. J Funct Foods 16:334–51.

Jaumot J, Gargallo R, de Juan A, Tauler R. 2005. A graphical user-friendly interface for MCR-ALS: a new tool for multivariate curve resolution in MATLAB. Chemometr Intell Lab Syst 76:101–10.

Jaumot J, Igne B, Anderson C, Drennen JK, De Juan A. 2013. Blending process modeling and control by multivariate curve resolution. Talanta 117:492–504.

Kamal M, Karoui R. 2015. Analytical methods coupled with chemometric tools for determining the authenticity and detecting the adulteration of dairy products: A review. Trends Food Sci Technol 46:27–48.

Kamruzzaman M, Makino Y, Oshita S. 2015. Rapid and non-destructive detection of chicken adulteration in minced beef using visible near-infrared hyperspectral imaging and machine learning. J Food Engr 170:8–15.

Kamruzzaman M, Makino Y, Oshita S. 2016. Hyperspectral imaging for real-time monitoring of water holding capacity in red meat. LWT - Food Sci Technol 66:685–91.

Kamruzzaman M, Sun DW, ElMasry G, Allen P. 2013. Fast detection and visualization of minced lamb meat adulteration using NIR hyperspectral imaging and multivariate image analysis. Talanta 103:130–6.

Klimkiewicz A, Mortensen PP, Zachariassen CB, van den Berg FW. 2014. Monitoring an enzyme purification process using on-line and inline NIR measurements. Chemometr Intell Lab Syst 132:30–38.

Li X, He Y. 2008. Discriminating varieties of tea plant based on Vis/NIR spectral characteristics and using artificial neural networks. Biosyst Engr 99:313–21.

Liao YT, Fan YX, Cheng F. 2010. On-line prediction of fresh pork quality using visible/near-infrared reflectance spectroscopy. Meat Sci 86:901–07.

Liao YT, Fan YX, Cheng F. 2012. On-line prediction of pH values in fresh pork using visible/near-infrared spectroscopy with wavelet de-noising and variable selection methods. J Food Engr 109:668–75.

Liu F, Ye X, He Y, Wang L. 2009. Application of visible/near infrared spectroscopy and chemometric calibrations for variety discrimination of instant milk teas. J Food Engr 93:127–33.

Liu Y, Sun X, Ouyang A. 2010. Nondestructive measurement of soluble solid content of navel orange fruit by visible–NIR spectrometric technique with PLSR and PCA-BPNN. LWT - Food Sci Technol 43:602–07.

Lohumi S, Lee S, Lee H, Cho B-K. 2015. A review of vibrational spectroscopic techniques for the detection of food authenticity and adulteration. Trends Food Sci Technol 46:85–98.

Lomiwes D, Reis MM, Wiklund E, Young OA, North M. 2010. Near infrared spectroscopy as an on-line method to quantitatively determine glycogen and predict ultimate pH in pre rigor bovine M-longissimus dorsi. Meat Sci 86:999–1004.

MacGregor JF, Bruwer M-J. 2008. A framework for the development of design and control spaces. J Pharmaceut Innov 3:15–22.

Madden HH. 1978. Comments on the Savitzky-Golay convolution method for least-squares-fit smoothing and differentiation of digital data. Anal Chem 50:1383–86.

Marković S, Poljanec K, Kerč J, Horvat M. 2014. Inline NIR monitoring of key characteristics of enteric coated pellets. Eur J Pharmaceut Biopharmaceut 88:847–55.

Meza-Márquez OG, Gallardo-Velázquez T, Osorio-Revilla G. 2010. Application of mid-infrared spectroscopy with multivariate analysis and soft independent modeling of class analogies (SIMCA) for the detection of adulterants in minced beef. Meat Sci 86:511–19.

Morsy N, Sun DW. 2013. Robust linear and non-linear models of NIR spectroscopy for detection and quantification of adulterants in fresh and frozen-thawed minced beef. Meat Sci 93:292–302.

Nicolai BM, Beullens K, Bobelyn E, Peirs A, Saeys W, Theron KI, Lammertyn J. 2007. Nondestructive measurement of fruit and vegetable quality by means of NIR spectroscopy: a review. Postharvest Biol Technol 46:99–118.

Ortiz-Somovilla V, España-España F, Gaitán-Jurado A, Pérez-Aparicio J, De Pedro-Sanz E. 2007. Proximate analysis of homogenized and minced mass of pork sausages by NIRS. Food Chem 101:1031-40.

Osborne BG, Fearn T, Hindle PH. 1993. Practical NIR spectroscopy with applications in food and beverage analysis. Harlow, UK: Longman Scientific and Technical.

Ozaki Y, McCluer WF, AA C. 2007. Near-infrared spectroscopy in food science and technology. Hoboken, New Jersey: John Wiley and Sons, Inc.

Pan TT, Sun DW, Cheng JH, Pu H. 2016. Regression algorithms in hyperspectral data analysis for meat quality detection and evaluation. Compreh Rev Food Sci Food Safety 15:529–41.

Park B, Chen Y, Hruschka W, Shackelford S, Koohmaraie M. 2001. Principal component regression of near-infrared reflectance spectra for beef tenderness prediction. Trans Am Soc Agric Engr 44:609–16.

Pasti L, Walczak B, Massart D, Reschiglian P. 1999. Optimization of signal denoising in discrete wavelet transform. Chemometr Intell Lab Syst 48:21–34.

Pierna J, Baeten V, Renier AM, Cogdill R, Dardenne P. 2004. Combination of support vector machines (SVM) and near-infrared (NIR) imaging spectroscopy for the detection of meat and bone meal (MBM) in compound feeds. J Chemometr 18:341–49.

Porep JU, Kammerer DR, Carle R. 2015. On-line application of near infrared (NIR) spectroscopy in food production. Trends Food Sci Technol 46:211–30.

Prieto N, Andrés S, Giráldez FJ, Mantecón A, Lavín P. 2008. Discrimination of adult steers (oxen) and young cattle ground meat samples by near infrared reflectance spectroscopy (NIRS). Meat Sci 79:198–201.

Prieto N, Juarez M, Larsen IL, Lopez-Campos O, Zijlstra RT, Aalhus JL. 2015. Rapid discrimination of enhanced quality pork by visible and near infrared spectroscopy. Meat Sci 110:76–84.

Prieto N, Ross DW, Navajas EA, Nute GR, Richardson RI, Hyslop JJ, Simm G, Roehe R. 2009. On-line application of visible and near infrared reflectance spectroscopy to predict chemical-physical and sensory characteristics of beef quality. Meat Sci 83:96–103.

Pullanagari RR, Yule IJ, Agnew M. 2015. On-line prediction of lamb fatty acid composition by visible near infrared spectroscopy. Meat Sci 100:156–63.

Reis MM, Rosenvold K. 2014. Early on-line classification of beef carcasses based on ultimate pH by near infrared spectroscopy. Meat Sci 96:862–69.

Rinnan Å, van den Berg F, Engelsen SB. 2009. Review of the most common pre-processing techniques for near-infrared spectra. TrAC - Trends Anal Chem 28:1201–22.

Roger J-M, Chauchard F, Williams P. 2008. Removing the block effects in calibration by means of dynamic orthogonal projection. Application to the year effect correction for wheat protein prediction. J Near Infrared Spectrosc 16:311–15.

Ropodi AI, Panagou EZ, Nychas G-JE. 2017. Multispectral imaging (MSI): A promising method for the detection of minced beef adulteration with horsemeat. Food Contl 73:57–63.

Ropodi AI, Pavlidis DE, Mohareb F, Panagou EZ, Nychas GJE. 2015. Multispectral image analysis approach to detect adulteration of beef and pork in raw meats. Food Res Intl 67:12–18.

Rust SR, Price DM, Subbiah J, Kranzler G, Hilton GG, Vanoverbeke DL, Morgan JB. 2008. Predicting beef tenderness using near-infrared spectroscopy. J Anim Sci 86:211–19.

Salguero-Chaparro L, Baeten V, Fernandez-Pierna JA, Pena-Rodriguez F. 2013. Near infrared spectroscopy (NIRS) for on-line determination of quality parameters in intact olives. Food Chem 139:1121–26.

Shackelford S, Wheeler T, Koohmaraie M. 2004. Development of optimal protocol for visible and near-infrared reflectance spectroscopic evaluation of meat quality. Meat Sci 68:371–81.

Siche R, Vejarano R, Aredo V, Velasquez L, Saldaña E, Quevedo R. 2016. Evaluation of food quality and safety with hyperspectral imaging (HSI). Food Engr Rev 8:306–22.

Srivichien S, Terdwongworakul A, Teerachaichayut S. 2015. Quantitative prediction of nitrate level in intact pineapple using Vis–NIRS. J Food Engr 150:29–34.

Tajammal Munir M, Yu W, Young BR, Wilson DI. 2015. The current status of process analytical technologies in the dairy industry. Trends Food Sci Technol 43:205–18.

Thennadil S, Martin E. 2005. Empirical preprocessing methods and their impact on NIR calibrations: a simulation study. J Chemometr 19:77–89.

Thissen U, Üstün B, Melssen WJ, Buydens LM. 2004. Multivariate calibration with least-squares support vector machines. Anal Chem 76:3099–105.

Tian Y, Wang Z, Han X, Hou H, Zheng R. 2014. Comparative investigation of partial least squares discriminant analysis and support vector machines for geological cuttings identification using laser-induced breakdown spectroscopy. Spectrochim Acta Part B: Atom Spectrosc 102: 52–57.

Togersen G, Arnesen JF, Nilsen BN, Hildrum KI. 2003. On-line prediction of chemical composition of semi-frozen ground beef by non-invasive NIR spectroscopy. Meat Sci 63:515–23.

Togersen G, Isaksson T, Nilsen BN, Bakker EA, Hildrum KI. 1999. On-line NIR analysis of fat, water and protein in industrial scale ground meat batches. Meat Sci 51:97–102.

Velardi SA, Hammouri H, Barresi AA. 2009. Inline monitoring of the primary drying phase of the freeze-drying process in vial by means of a Kalman filter based observer. Chem Engr Res Des 87: 1409–19.

Wold JP, Bjerke F, Måge I. 2016. Automatic control of fat content in multiple batches of meat trimmings by process analytical technology. Fleischwirtschaft Intl 31:69–74.

Wold JP, Johansen IR, Haugholt KH, Tschudi J, Thielemann J, Segtnan VH, Narum B, Wold E. 2006. Non-contact transflectance near infrared imaging for representative on-line sampling of dried salted coalfish (bacalao). J Near Infrared Spectrosc 14:59–66.

Wold JP, O'Farrell M, Hoy M, Tschudi J. 2011. On-line determination and control of fat content in batches of beef trimmings by NIR imaging spectroscopy. Meat Sci 89:317–24.

Wu W, Walczak B, Massart D, Heuerding S, Erni F, Last I, Prebble K. 1996. Artificial neural networks in classification of NIR spectral data: design of the training set. Chemometr Intell Lab Syst 33:35–46.

Xiong Z, Sun D-W, Pu H, Zhu Z, Luo M. 2015. Combination of spectra and texture data of hyperspectral imaging for differentiating between free-range and broiler chicken meats. LWT - Food Sci Technol 60:649–55.

Xiong Z, Sun D-W, Zeng X-A, Xie A. 2014. Recent developments of hyperspectral imaging systems and their applications in detecting quality attributes of red meats: A review. J Food Engr 132:1–13.

Zamora-Rojas E, Perez-Marin D, De Pedro-Sanz E, Guerrero-Ginel JE, Garrido-Varo A. 2012. Handheld NIRS analysis for routine meat quality control: Database transfer from at-line instruments. Chemometr Intell Lab Syst 114:30–35.

Zeaiter M, Roger J, Bellon-Maurel V. 2006. Application to NIR-based monitoring of wine fermentations. Chemometr Intell Lab Syst 80: 227–35.