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Applications of Near-infrared Spectroscopy in Food Safety Evaluation and Control: A Review of Recent Research Advances

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Food safety is a critical public concern, and has drawn great attention in society. Consequently, developments of rapid, robust, and accurate methods and techniques for food safety evaluation and control are required. As a nondestructive and convenient tool, near-infrared spectroscopy (NIRS) has been widely shown to be a promising technique for food safety inspection and control due to its huge advantages of speed, noninvasive measurement, ease of use, and minimal sample preparation requirement. This review presents the fundamentals of NIRS and focuses on recent advances in its applications, during the last 10 years of food safety control, in meat, fish and fishery products, edible oils, milk and dairy products, grains and grain products, fruits and vegetables, and others. Based upon these applications, it can be demonstrated that NIRS, combined with chemometric methods, is a powerful tool for food safety surveillance and for the elimination of the occurrence of food safety problems. Some disadvantages that need to be solved or investigated with regard to the further development of NIRS are also discussed.

Keywords NIRS, food industry, safety, chemometric, freshness, authentication, adulteration, poison detection, illegal treatments

INTRODUCTION

Food safety problems are frequently confronted; therefore, there has been increasing concern from consumers, retailers, and regulatory authorities on the safety of foods. Although some quality- and safety enhanced technologies such as cooling (Hu and Sun, 2000; Wang and Sun 2001), freezing (Delgado et al. 2009), drying (Sun 1999; Sun and Woods 1993, 1994, 1997; Sun and Byrne 1998; Delgado and Sun 2002), and edible coating (Xu et al. 2001) are available, in addition, some quality- and safety-control procedures are also in place using traditional techniques, such as instrumental methods and physicochemical and microbiological procedures, these procedures

are normally destructive, laborious, complex, and time-consuming and, consequently, result in limitations for practical uses especially for on-line applications. Therefore, there is a great need to establish rapid, and advanced nondestructive methods such as computer vision (Du and Sun, 2005; Valous et al., 2009), spectroscopy and hyperspectral imaging (Kamruzzaman et al., 2011; 2012; ElMasry et al., 2011, 2012) that can be practically and effectively used in the food industry. Over the past few years, near-infrared spectroscopy (NIRS) has been demonstrated to be one of the most efficient and promising techniques for monitoring and controlling product quality and safety in agri-food processing (Sun, 2009; Bao et al., 2014; Ouyang et al., 2013; Wu et al., 2012; Magwaza et al., 2012; Shen et al., 2012; Hódsági et al., 2012; Lin et al., 2012; Liu et al., 2011; Abdel-Nour, 2011). Compared to traditional detection techniques, NIRS technology requires less detection time, little or no tedious sample preparation, and shows good adaptability. NIR covers the range of the electromagnetic spectra between 780 and 2500 nm (Nicolai et al.,

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Table 1 Application fields of NIRS in food safety evaluation and control categorized by species in the recent 10 years

Application fields	References
Meat and meat products	Alomar et al., 2003; Windham et al., 2003; Cozzolino & Murray 2004; Berzaghi et al., 2005; Ortiz-Somovilla et al., 2005; Berzaghi et al., 2006; Pla et al., 2007; Ballin et al., 2009; Prieto, Ross et al., 2009; Del Moral et al., 2009; Ballin, 2010; Monroy et al., 2010; Chen et al., 2011b; Grau et al., 2011; Mamani-Linares et al., 2012; Morsy & Sun 2012; Zamora-Rojas et al., 2012; Alamprese et al., 2013; Barbin et al., 2013
Fish and fishery products	Cozzolino et al., 2002; Heia et al., 2003; Lin et al., 2003; Uddin & Okazaki 2004; Nilsen & Esaiassen 2005; Uddin et al., 2005b; Uddin et al., 2005a; Cozzolino et al., 2005a; Cozzolino et al., 2005b; Cakli et al., 2006; Lin et al., 2006; Gayo, 2006; Gayo et al., 2006; Cakli et al., 2007; Uddin et al., 2007; Gayo & Hale 2007; Yang et al., 2008; Sivertsen et al., 2011; Tito et al., 2012; Fasolato et al., 2012; Kimiya et al., 2013; Ottavian et al., 2013
Fruits and vegetables	Xie et al., 2007; Di Egidio et al., 2009; Sánchez et al., 2009; Kurz et al., 2010; Pérez-Marín et al., 2011; Xue et al., 2012; Salguero-Chaparro et al., 2012; Agelet et al., 2013
Edible oils	Marquez et al., 2005; Yang et al., 2005; Wang et al., 2006; Sinelli et al., 2010; Mignani et al., 2011; Zhu et al., 2011; Luo et al., 2012; Kuligowski et al., 2012; Luna et al., 2013
Dairy and dairy products	Borin et al., 2006; Kasemsumran et al., 2007; Mauer et al., 2009; Balabin & Smirnov 2011; Hsieh et al., 2011
Cereals and cereals products	Cocchi et al., 2006; Li et al., 2008; Fernández-Ibañez et al., 2009; Yuan et al., 2011; Shao et al., 2011; Dachoupakan Sirisomboon et al., 2013
Honey	Mishra et al., 2010; Zhu et al., 2010; Chen et al., 2011a
Coffee	Pizarro et al., 2007; Ebrahimi-Najafabadi et al., 2012
Wine	Ferrari et al., 2011
Spirulina powder	Wu et al., 2011
Corn meal, soya bean meal	Gaspardo et al., 2012; Haughey et al., 2013
Irradiated sucrose	Gong et al., 2012
Instant milk teas	Liu et al., 2009
Instant noodles	Liu & He 2008
Distilled alcoholic beverages	Pontes et al., 2006

2007). The spectra can be recorded in reflection, transmission, or intertransmittance modes providing complex chemical and physical information related to the vibration behavior of molecular bonds such as C—H, O—H, and N—H.

NIRS analysis has been successfully applied in food safety analysis and prediction, and some relevant information is displayed in Table 1. In the meat industry, some researchers have focused on the adulteration of meats using NIRS technique (Morsy & Sun, 2012; Alamprese et al., 2013). The evaluation of fish and fishery product quality was also investigated by several researchers, and many studies about NIRS applications in this field have been published in recent years (Uddin & Okazaki, 2004; Tito et al., 2012). In addition, NIRS offers many possibilities for other food studies such as identification and constituent analysis of fruits (Kurz et al., 2010), oils (Kuligowski et al., 2012) and dairy products (Balabin & Smirnov, 2011). Discrimination and quantification of adulterated olive oils enabled correct classification levels of up to 99.7% (Mignani et al., 2011). Determination of free fatty acids (FAs) and moisture in fish oils was studied and low standard errors of prediction (SEP) and a high correlation coefficient (R) of 0.98 were obtained (Cozzolino et al., 2005b). Moreover, this technology has been applied to evaluate freshness detection of beef (Prieto et al., 2008), maturity and textural properties of tomatoes (Flores et al., 2009), acidity and peroxide index in edible oils (Yang et al., 2005), rheological parameters in wheat grain (Yuan et al., 2011), and more. Moreover, several authors have explored the feasibility of NIRS to classify

2010; Chen et al., 2012; Zamora-Rojas et al., 2012) or authenticate foods (Cozzolino & Murray, 2004; Marquez et al., 2005; Casale et al., 2010; Di Egidio et al., 2011; Casale et al., 2012). The rapid development of NIRS has brought innovation to food safety evaluation and control. However, the molecular overtone and combination bands (O—H, C—H, C—HO, and N—H) in NIR are typically very broad, and it is difficult to assign certain features to specific chemical components as the chemical structures are composed of numerous and complex diverse chemical bonds. Chemometric techniques are necessary to facilitate the extraction of desired spectral information. With the development of chemometrics, NIRS becomes more popular and attracts more attention from food researchers. An excellent review showing the ability of NIRS to predict meat chemical composition and quality can be found in the studies conducted by Prieto et al. (2009). Besides this, Nicolai et al. (2007) and Lin & Ying (2009) have reviewed the applications of NIRS in predicting food quality and safety of fruits and vegetables. Moreover, Huang et al. (2008) provided an update on monitoring the quality of foods and beverages. In addition, Alishahi et al. (2010) have reviewed the possibility of NIRS in differentiating transgenic and nontransgenic foods, feeds, and more. These review papers are mainly focused on quality evaluations. No paper is available to specifically address the application of NIRS on food safety surveillance. Therefore, the objective of this paper is to introduce the fundamentals of NIRS and mainly focus on its applications in different aspects of food safety evaluation and control.

FUNDAMENTALS OF NIRS

Principle of NIRS

The spectral range for NIR covers a waveband range between 780 and 2500 nm. NIR spectra are complex due to highly overlapping and weak absorption bands associated with overtones and combinations of vibrational bonds. In particular, overtones and combinations of the vibrations of C—H, O—H, N—H, and C=O as well as some other bonds can be observed in the NIR range, making it possible for measurements of various structures. When radiation penetrates the sample, the radiation is reflected, absorbed by molecular bonds, and/or transmitted, resulting in energy changes of light, which, in turn, can reflect some featured chemical bonds and, thus, the characteristics of tested products.

Generally, a NIRS system comprises four components as illustrated in Fig. 1: light source, light-isolating mechanisms, detector, and sampling devices (Wang & Paliwal, 2007). The light segmentation system is vital to spectrometers and, therefore, NIR instrumentation is sorted according to the type of monochromator (Nicolai et al., 2007). Modern NIR spectrometers can be mainly categorized as light-filter instruments, scanning monochromator instruments, light-emitting diode (LED) instruments, Fourier transform (FT) NIR instruments, array-detecting instruments, acoustic optic tunable filter (AOTF) instruments, and liquid crystal tunable filter (LCTF) instruments (Nicolai et al., 2007; Wang & Paliwal, 2007). The monochromator of a light filter instrument is a wheel made of a few filters, whose spectral resolution is somewhat low but the sampling rate is high. In a scanning monochromator instrument, a grating or a prism is usually employed as the light-separation component. The wavelength separator rotates so as to separate the radiation, which forces on different wavelengths to reach the detector subsequently; its spectral resolution is high. In a light-emitting diode (LED) instrument, an LED is

used as the light source and is able to transform electronic energy into radiation directly. It is efficient and durable. Besides this, a laser diode (LD) has also been adopted in the last few decades in NIRS instrumentation. An FT NIR instrument, commonly used in the food industry, includes a Michelson interferometer or a polarization interferometer as the core element to generate modulated light. Then, the light signal is transformed into a spectrum by means of Fourier transform. In array-detecting instruments, an array detector involves a photodiode array (PDA) and a charge-coupled device (CCD). Usually, the fixed grating focuses the dispersed radiation onto an array of silicon of CCD or PDA in the short wavelength range of 350 to 1100 nm or InGaAs-based (a type of semiconductor materials, owing faster transmission speed than Silicon semiconductor material) PDA in the long wavelength range of 1100 to 2500 nm. Due to its characteristics of high stability, excellent interference immunity, and fast scanning speed, it is particularly suitable for on-line and field measurements. On the other hand, AOTF instruments are based on acousto-optic diffraction principles, and different wavelengths of light are produced by utilizing an optical band-pass filter. Finally, in a LCTF instrument, a birefringent filter is used to transmit a selected wavelength of light and exclude others. LCTF is prominent because it can help produce high-quality images and spectra covering a wide range of wavelengths (Wang & Paliwal, 2007; Nicolai et al., 2007).

In selecting a proper set of equipment, instrumentation with higher configuration, such as high spectral resolution, large scanning ranges, and adjustable scanning speed, are the priorities for scientific research. Although used for monitoring a production line, the NIRS systems should be designed for explicit work, as the application for commercial utilization is usually predetermined (Lin & Ying, 2009). However, the features of the abovementioned components of NIRS instrumentation determine the entire performance, which should be taken into account when assembling such a system. In recent years particularly, the evolution of hardware and software has allowed NIRS instruments to be transformed into more portable and practical devices (Nicolai et al., 2007).

There are three modes of data collection (Wu & Sun, 2013), namely, reflectance (Fig. 2-a), transmittance (Fig. 2-b), interactance (Fig. 2-c). The choice of a suitable collection mode relies on the type of sample and the constituents to be tested, which determines the entire results of the attempt. In reflectance mode, the radiation reflected from the sample surface and the detector is situated at the same side of the light source to capture the reflected light from the sample, which is usually used for solid or granular samples. Tests in transmittance mode measure the amount of light transmitted through the sample, which is usually small but can carry more valuable information in it (Schaare & Fraser, 2000). In transmittance mode, the detector is located at the opposite side of the illumination, and such a mode is normally used for the analysis of liquid samples and certain solid samples such as grains, meat, dairy, and so on. Interactance mode is a combination of reflectance and

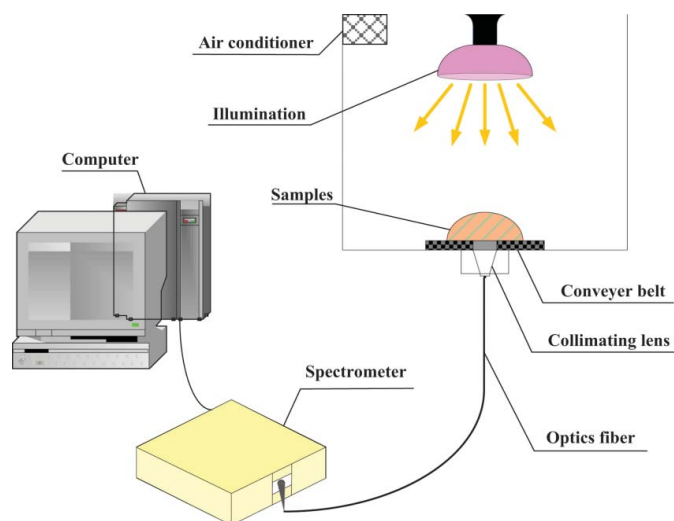


Figure 1 Components of a NIRS system.

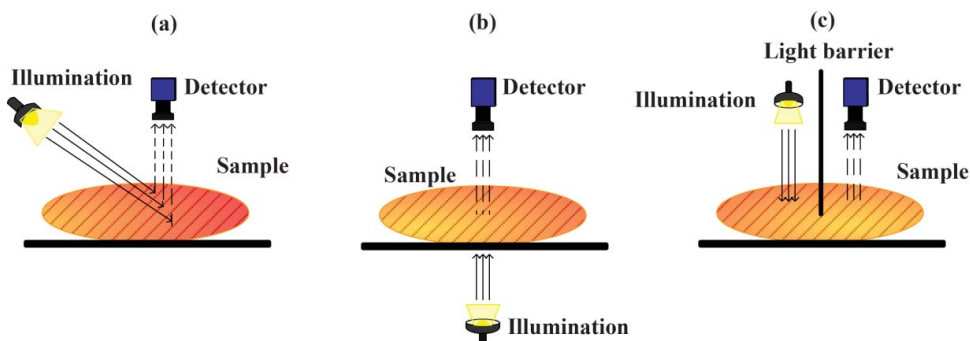


Figure 2 Modes of data acquisition in NIRS system. (a) Reflectance mode, (b) transmittance mode, and (c) interactance mode.

transmittance, in which the light source and the detector are positioned parallel to each other on the same side of the tested product (Nicolai et al., 2007). Large samples such as whole fruits are suited for this type of measurement. Furthermore, research has shown that, compared with reflectance and interactance modes, transmittance measurements facilitated better classification accuracies (Wang et al., 2011) and it has been shown to perform better for internal disorder detection (Fu et al., 2007). For measuring SSC, density, and flesh hue of *Actinidia chinensis*, interactance mode performed best followed by transmission mode and reflectance by turn (Schaare & Fraser, 2000). The spectra in Fig. 3 illustrate the differences between the three spectral modes. Clearly, the most obvious distinction is

that the transmitted light is only limited to the spectral range of 700 to 950 nm approximately, and the range of the spectral amplitude is wide in transmittance mode (Schaare & Fraser, 2000).

The typical procedure for analyzing food products by means of NIRS can be summarized into the following five steps as shown in Fig. 4: (1) choosing a NIR spectrometer and relevant accessories for detection; (2) selecting representative samples; (3) acquiring NIR data and determining chemical or physical references; (4) establishing and validating a model; and (5) predicting the target parameters of unknown samples or characterizing the nature of the tested samples. Of particular interest in the whole process, is that it is essential to use the appropriate penetration depth in different spectral ranges when

selecting the measurement device. Lammertyn et al. (2000) defined the penetration depth as the slice thickness for which the diffuse reflectance spectra were significantly different from those of a slice of infinite thickness. They found that light, in the 700 to 900 nm range, could penetrate a depth of up to 4 mm and, in the 900 to 1900 nm range, could penetrate to approximately 2–3 mm depth for apples. As the light in the short wavelength range has higher frequency and stronger energy, it is easier for it to penetrate objects compared with that in the long wavelength range. However, for mandarin or other thick-skinned fruits, the thicker skin poses a large barrier, which limits the potential of detecting internal defects and obtaining high accuracy in reflectance or interactance mode (Fraser et al., 2003). In this case, transmitted light in high intensity could possibly detect the surface or core properties, depending on specific applications (Nicolai et al., 2007).

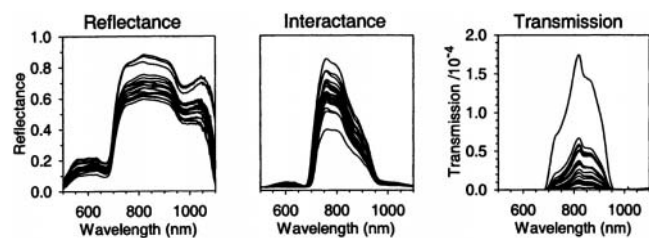


Figure 3 Typical reflectance, interactance, and transmission spectra. The vertical transmission scale is only approximate and the vertical interactance axis shows raw intensity on an arbitrary scale. The reflectance spectra range from 450 to 1100 nm, interactance spectra from 520 to 1100 nm, and transmission spectra from 690 to 1080 nm (Schaare & Fraser, 2000).

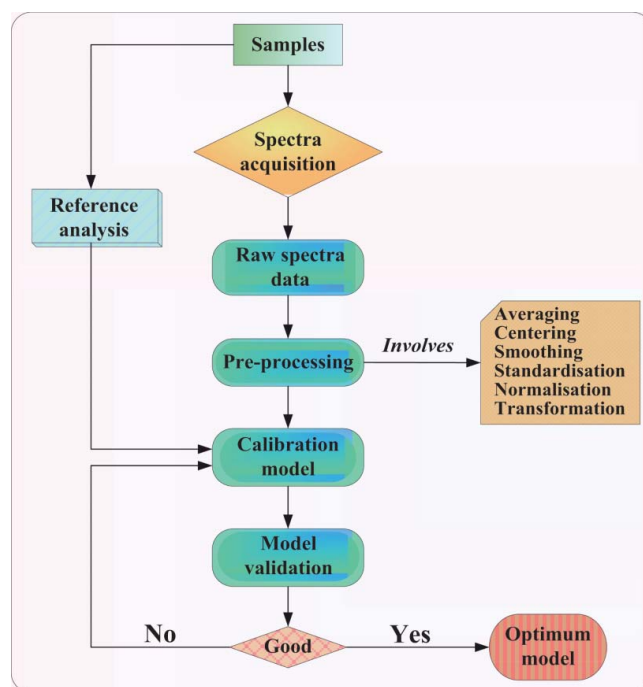


Figure 4 A series of steps in the procedure of NIRS analysis from sampling to an optimal model for prediction.

Chemometrics

NIRS for food quality assessment relies on collecting spectra of tested products and relating spectral signatures with sample characteristics by establishing calibration models (Nicolai et al., 2007; Pojić & Mastilović, 2013). However, NIR spectra contain large quantities of data that require processing; therefore, chemometrics (a combination of statistical and mathematical sciences) is usually used for extracting useful information, which can significantly enhance the potential applications of NIRS. Chemometrics covers a wide range of methods involving spectral data preprocessing, building calibration models for qualitative and quantitative analysis, and model transfer (Cen & He, 2007). In particular, apart from the desired spectral sample signatures, the data obtained from NIR usually contain plenty of noise and redundant information such as background information; therefore, preprocessing is needed to remove these redundancies.

Common methods used for preprocessing are averaging, centring, smoothing, standardization, and normalization. Specifically, averaging can be used to reduce thermal noise when acquiring spectrum, and as for the obtained spectra it is usually used for smoothing the spectra. Centring, namely mean centring, aims to subtract the average value from every variable in the first step of preprocessing, which ensure the results will be much more interpretable. Smoothing is used to improve the quality of the NIR spectra by removing noise, mainly consisting of moving average filters and applying the Savitzky–Golay algorithm (Næs et al., 2004). Standardization is proposed to divide the spectra by standard deviation at every wavelength. However, it is seldom used for NIRS in that noise on a variable with a small standard deviation may generate a less trustworthy model. When it comes to normalization, multiple scatter correction (MSC) is taken, for example. It has been dedicated to diminish effects in the spectra caused by physical and chemical (extended multiple scatter correction, EMSC) effects. Besides, standard normal variate correction (SNV) allows each individual spectrum to be normalized to zero mean and unit variance (Nicolai et al., 2007).

Concerning linear regression techniques, multivariate regression (MLR), principal component regression (PCR), and partial least squares regression (PLSR) are three typical approaches. MLR is supposed to build a connection between the $n \times N$ spectral matrix X ('X-variables'), with the number of spectra (n) and wavelengths (N) and the $n \times 1$ vector of reference values y ('Y-variables'). As the number of samples is generally much smaller than that of variables, usually, MLR is not used for full spectral measurements. When confronted with the high colinearity of the spectra, MLR may not perform well and could even give rise to overfitting and decrease of robustness of the calibration models. However, PCR is the integration of PCA and MLR by introducing the decomposed X (PCA) to a MLR model, only a few principal components (PCs; or latent variables) are used to replace the original variables. PLS decomposes the spectral matrix and the y -vector(s)

simultaneously, thereby involving Y -data in the operation. In addition, it allows a smaller number of latent variables than PCR and can also be extended to simultaneously predict several quality attributes which are called PLS2 (Nicolai et al., 2007).

With respect to nonlinear regression techniques, the artificial neural network, (ANN) is the most popular method, composed of three layers neurons involving the input, hidden, and output layers; it is widely used for classification, which also has shown better aptitude than linear techniques (Hahn et al., 2004). Moreover, kernel-based techniques have been popular recently thanks to the interpretation of the calibration model compared with ANNs. Among these, least-squares support vector machines (LS-SVM) is a representative kernel-based multiple regression procedure, which greatly improved the robustness of the calibration models by introducing a second tuning parameter Γ that can penalize large values of the regression coefficients (Nicolai et al., 2007).

Furthermore, model validation and accuracy measurement is a significant process. The R^2 value represents the proportion of explained variance of the response variable in the calibration (R_C^2), validation (R_{CV}^2) and (R_P^2) prediction sets. The prediction error of a calibration model is denoted as the root mean square error (RMSE) for calibration (RMSEC), cross validation (RMSECV), and prediction (RMSEP), respectively. In some papers, standard error is used instead of the RMSE (Ortiz-Somovilla et al., 2005). The RPD is defined as the ratio of the standard deviation of the response variable to the RMSEP or RMSECV. Moreover, an RPD value over 1.5 and 2 indicates that the model can only differentiate between low and high values, whereas a value between 2 and 2.5 means that it can perform predictions roughly, and a value between 2.5 and 3 or more is indicative of fairly good prediction accuracy (Nicolai et al., 2007).

RECENT APPLICATIONS OF NIRS FOR FOOD SAFETY EVALUATION AND CONTROL

The potential of NIRS has been successfully demonstrated in the food industry. Although more studies have been conducted in food quality analysis, the application of NIRS in food safety evaluation and control is increasing, which will be specifically discussed in the following sections. Figure 5 presents the extent of published articles quoted in this paper in recent years involving different application fields (including freshness determination, authentication and adulteration, poison detection, and illegal treatments).

Meat and Meat Products

Food authenticity is an emerging area of concern not only for consumers, but also for producers and distributors. With regard to meat products, the determination of meat

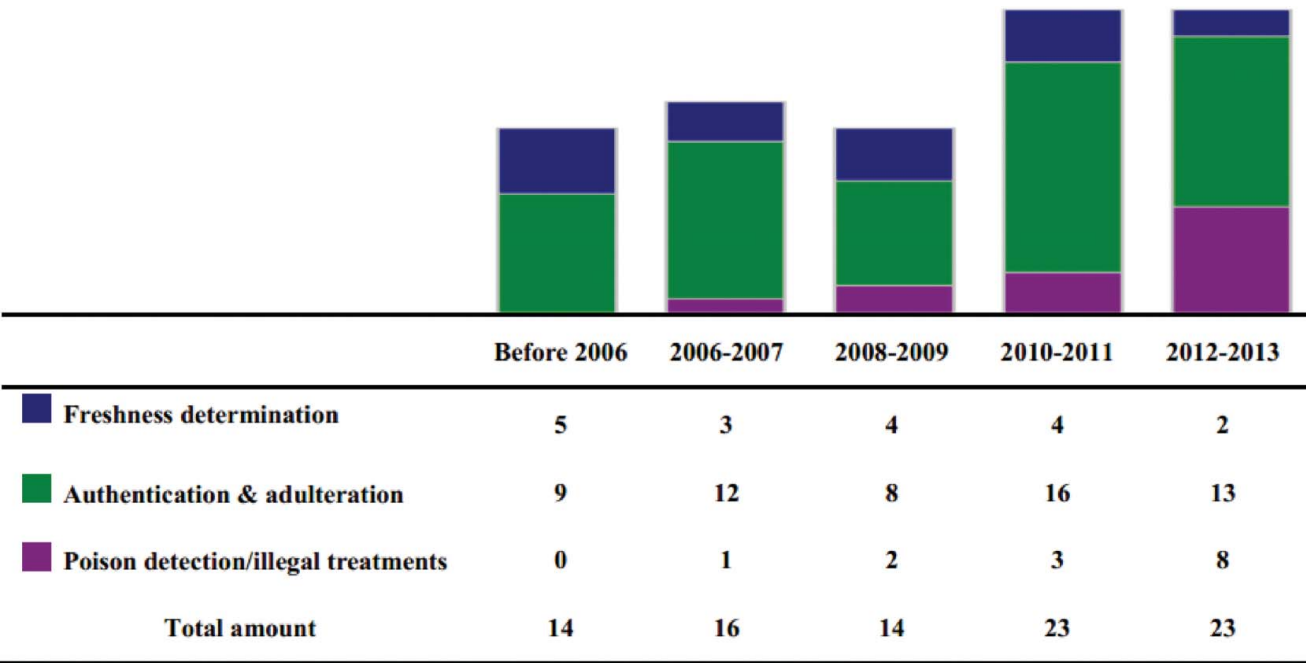


Figure 5 Chart demonstrating the number of published articles cited in the current paper, involving studies utilizing NIRS in three major application areas up to 2013.

authenticity and the detection of adulteration are major issues in the meat industry, and they are attracting increasing attention. Meat adulteration may cause damage to human health and affect public trust for the whole meat industry. Moreover, meat adulteration can cause some religious problems as, in some countries, the consumption of certain meats (e.g., pork) is proscribed for religious reasons. In practice, a considerable number of fraudulent replacements have occurred. For the benefit of consumers and to prevent unfair competition in the trade of meat products, rapid and reliable methods that allow distinguishing adulteration would be of significant importance. In recent years, many investigators have applied various techniques to identify meat types, as comprehensively reviewed by Ballin et al. (2009). Immunological, enzymatic, electrophoretic, and DNA-based procedures have been applied, but all these methods are laborious and technically demanding. The development of easy, rapid, and sensitive methods is, thus, still needed for implementing meat quality and safety control. NIRS being rapid, easy, and nondestructive, it has been demonstrated to have potential for addressing some authenticity issues in meat products. Many studies have been conducted on meat adulteration by NIRS in the past decades, and satisfactory results were obtained (Ballin et al., 2009; Ballin, 2010).

The adulteration of beef is a prime concerns because beef is a type of popular meat with a high price in most countries. In order to reap huge profits, some retailers tend to provide customers with beef meat being partially substituted with other meat species of lower quality or even provide beef meat after some illegal treatments. There are many reports on the

discrimination of beef from other types of meat (Cozzolino & Murray, 2004; Mamani-Linares et al., 2012) and on identification of illegal growth promoters in beef (Berzaghi et al., 2006). In all cases, highly accurate classifications were largely achieved, indicating that NIRS is a simple and reliable technique to classify meat species. Mamani-Linares et al. (2012) employed visible near-infrared spectroscopy (VIS-NIRS) to differentiate between beef, llama, and horse meat by analyzing reflectance spectra of the minced meat. In addition, they investigated the differentiation of meat juice where the spectra were collected in transreflectance mode in the range of 400 to 2500 nm. An accuracy of over 89% was obtained based on partial least squares regression (PLSR) analysis, and use of transreflectance spectra of meat juice allowed slightly better identification results for llama and horse meat samples. However, more robust models required inclusion of more samples of different years, geographic origins, animal breeds, production systems, and muscle types, which were expected to cover a broad range of variations so that the model subsequently built could be representative and adaptive. NIR reflectance spectroscopy was applied for differentiating between different types of cattle meat involving various breeds, muscle types, and ages. Results demonstrated that NIRS could correctly identify and discriminate beef samples based on their differences in intramuscular fat and water contents (Alomar et al., 2003). For adulteration detection, Morsy and Sun (2012) applied VIS-NIRS (400–2500 nm) to detect adulterants in both fresh and frozen-thawed minced beef. PLSR models were established and coefficients of determination for prediction

(R_p^2) of 0.96, 0.94, and 0.95 with standard error of prediction (SEP) of 5.39, 5.12 and 2.08% (w/w) were obtained for fresh beef adulterated with pork, fat trimming and offal, respectively. For frozen-thawed minced beef, R_p^2 of 0.93, 0.82 and 0.95 with SEP of 7.11, 9.10, and 2.38% (w/w) were achieved for adulteration with pork, fat trimming, and offal, respectively. By linear discriminant analysis (LDA), partial least squares discriminant analysis (PLS-DA), and nonlinear regression models (exponential regression), adulterated and unadulterated minced beef was differentiated with accuracy up to 100%. The study demonstrated the possibility that VIS-NIRS could detect and quantify the amount of adulterants added to the minced beef with acceptable precision and accuracy. In addition, Alamprese et al. (2013) tested the feasibility of ultra-violet-visible (UV-VIS), NIR, and mid-infrared (MIR) spectroscopy in detecting turkey meat in minced beef with the aid of PCA, LDA, and partial least squares (PLS). Good results were attained by NIR and MIR spectroscopy that could be further improved when combined with UV-VIS. Furthermore, in order to suppress the use of hormones and successfully identify treated animals, NIR in the region between 1100 and 2498 nm was tested to determine illegal growth promoters. Modified partial least squares (MPLS) was introduced to build calibration models with R^2 of 0.77 and 0.76 for the calibration and validation datasets on freshly ground meat, respectively (Berzaghi et al., 2006).

Although the majority of studies focused on beef adulteration, some attempted to emphasize the quality and safety evaluation of pork and chicken. McDevitt et al. (2005) attempted to discriminate pork and chicken from different breeds and genotypes by NIRS. Spectra from 350 to 2500 nm were processed by ANN, and a correct classification of over 95% was achieved. In addition, the capacity of NIRS was studied in the classification of Duroc and Iberian pork by artificial neural networks according to various feeding regimes and qualities (Del Moral et al., 2009). A total of 300 carcass samples of Iberian pigs were raised under different feeding conditions ("Acorn", "Recebo", and "Feed"), and they were analyzed by a handheld micro-electromechanical system (MEMS)-based spectrophotometer (1600–2400 nm). The best classification rates of 93.9%, 96.4%, and 60.6% were achieved for "Acorn", "Recebo", and "Feed" feeding conditions, respectively (Berzaghi et al., 2005; Monroy et al., 2010; Zamora-Rojas et al., 2012). Moreover, Iberian pork sausages from meat mixtures were also detected by using NIRS (400–1700 nm). The samples were divided into fresh ($N = 75$) and dry-cured ($N = 75$) sausages and discriminant analysis was applied to achieve the best results (fresh products: $R_C = 98.3\%$, $R_{CV} = 60\%$; dry-cured sausages: $R_C = 91.7\%$, $R_{CV} = 80\%$). On the other hand, by using samples of meat mixtures, good models were built for classification (fresh products: $R_C = 98\%$, $R_{CV} = 73.3\%$, $SECV = 4.7$; dry-cured sausages: $R_C = 99\%$, $R_{CV} = 93.3\%$, $SECV = 5.9$) (Ortiz-Somovilla et al., 2005). Another investigation was conducted by Chen et al. (2011b), where FT NIR spectroscopy (400–2500 nm) was combined with linear and

nonlinear classification algorithms to differentiate between pork of different storage times. Among different methods such as LDA, K-nearest neighbors (KNN), and back-propagation artificial neural network (BP-ANN), BP-ANN models proved to be the best with discrimination rates of 99.26% and 96.21% in the training and prediction sets, respectively. In addition, NIRS was used to differentiating between meat from beef, lamb, pig, and chicken with the aid of PCA and PLS. Finally, the model correctly authenticated and identified different meat muscle species with over 80% accuracy (Cozzolino & Murray, 2004). The results showed the potential of VIS and NIR spectra as an objective and rapid method for authentication and identification of meat muscle species.

Fecal contamination on food surfaces and loss of freshness are two main issues in food safety evaluations. The loss of freshness in a food matrix is always an indicator of unsuitability of food for consumption. Fecal or ingesta contamination of poultry meat is also of great concern. VIS-NIRS was initially demonstrated to be effective for spoilage detection and identification of feces on chicken breast muscles and carcasses (Windham et al., 2003; Alexandrakakis et al., 2012). Windham and his co-workers developed a classification model by PCA with optimal wavelengths of 434, 517, 565, and 628 nm, and this model was able to identify contaminated parts with a success rate of 95% on the basis of fecal color and myoglobin and/or hemoglobin content of the uncontaminated breast skin. Previous study showed that for chicken muscles, the 430 and 635 nm bands were mainly resulted from deoxymyoglobin and sulfmyoglobin, respectively, and bands at 545 and 575 nm were related to oxymyoglobin species in different molecular vibrations (Liu & Chen, 2000). Loss of meat freshness is followed by a complex combination of microbiologic, chemical, and physical spoilage processes. Various methods have been developed for freshness assessment based on the measurement of postmortem deteriorative changes associated with sensory quality, microbial growth, and chemical changes, such as pH or total volatile basic nitrogen (TVB-N) and the parameter K_1 . Concretely, the K value is a good indicator for evaluating freshness quality and shelf-life, defined as the ratio (%) of the total amount of inosine and hypoxanthine to that of ATP-related compounds, with K_1 being a simplified K value (Cheng et al., 2013b). Grau et al. (2011) aimed to predict the freshness of packaged sliced chicken breast by VIS and NIRS. The spectra obtained from images in the visible and SW-NIR (700–1100 nm) range have been related to sample storage time, where the best wavelengths for modeling freshness were 413, 426, 449, 460, 473, 480, 499, 638, 942, 946, 967, 970, and 982 nm. The loss of freshness has mainly been associated with the increase in the values of TVB-N, parameter K_1 , pH, and water activity (a_w). In addition, a linear connection was found between the optimal wavelengths and the parameters involving microbiologic counts, K_1 , and T-VBN indices. Most importantly, microbial contamination is crucial due to its leading to a decrease of the whole quality of the product, which is affected by temperature, water content, and more. Barbin and

his co-workers developed a NIR hyperspectral imaging system (900–1700 nm) to determine total viable count (TVC) and psychrotrophic plate count (PPC) in chilled pork during storage. The best results were obtained by PLSR with R^2 of 0.86 and 0.89 for log (TVC) and log (PPC) for the validation models, respectively (Barbin et al., 2013).

Some other research has been conducted to shed more insight into the rapid evaluation of informative parameters of meat products, such as FA content of rabbit meat (Pla et al., 2007), which was useful in differentiating between rabbit meat produced under conventional and organic production systems. Meat of the organic source had a lower content of monounsaturated FA (30.54% vs. 34.64%) and higher amount of polyunsaturated FA (27.28% vs. 23.66%) than rabbit meat from the conventional system, whereas the saturated FA content was similar (42%) in both groups. The discriminant model correctly classified rabbit meats between conventional and organic produced rabbits with a classification rate as high as 98%.

Overall, the abovementioned studies have confirmed the ability of NIRS to perform authentication and adulterant detection on meat and meat products. Moreover, meat samples of different breeds, ages, origins, and textures can be further explored by more accurate and robust models.

Fish and Fishery Products

Quality and safety is important for perishable foods such as fish and fishery products. A large proportion of the world's food products are lost annually as a result of microbial spoilage. When fish die, a series of postmortem physical and chemical changes take place, including the breakdown of cellular structures and endogenous enzyme autolysis, due to the growth of microorganisms. These endogenous and microbial processes result in fish spoilage and the product, thus, fails to meet consumers' expectations. Therefore, fish quality assessment is essential for the safety of fishery products during transportation, storage, and processing. Traditional methods for the assessment of fish quality are subjective, invasive and time consuming. How to quickly and objectively evaluate fish quality has become an urgent issue to be resolved in the fish-processing industry. NIRS provides fast and nondestructive measurements and potentially can be used for real-time assessment of bacterial loads on fish (Cheng et al., 2013a).

Freshness is an important microbiologic property of fish that makes a major contribution to the quality of fish and fishery products. Loss of freshness is followed by a complex combination of microbiologic, chemical, and physical spoilage processes. The government and consumers are paying more and more attention to the detection of fish freshness. Several researchers (Cozzolino et al., 2002; Cakli et al., 2006; Cakli et al., 2007; Uddin et al., 2007) have explored the feasibility of using VIS/NIRS for determinations of fish freshness. Based on these studies, VIS spectroscopy was applied for freshness

evaluation of frozen stored cod as compared to the freshness determined by sensory analyses (Heia et al., 2003; Nilsen & Eisaassen, 2005). Subsequently, for a similar purpose, Sivertsen et al. (2011) used a VIS/NIRS system equipped with a handheld interactance probe and an imaging spectrometer. They found the system was excellent to discriminate between fresh and frozen-thawed cod fillets and to assess the freshness as days on ice. The results showed that freshness as days on ice can be measured with an accuracy of 1.6 days on individual fillets, and the oxidation of hemoglobin and myoglobin during freezing-thawing and cold storage on ice proved to be the main reasons for the variations of the obtained spectra in the VIS region.

Occurrence of spoilage usually induces changes in physical characteristics. Therefore, rapid and accurate detection of spoilage and assessment of microbial contamination during fish processing are necessary to ensure fish quality. Some reports have addressed the use of spectroscopic methods for spoilage detection and microbial quantification (Lin et al., 2006). More recently, Tito et al. (2012) and Kimiya et al. (2013) studied the feasibility of NIRS in determining microbial numbers on Atlantic salmon noninvasively. In the first study, fresh salmon fillets and those stored at 4 °C for nine days could be clearly separated by PCA. PLSR was used for establishing prediction models and the calibration was satisfactory ($R^2 = 0.95$ and $RMSE = 0.12 \log_{10}$ colony forming units/g). The results illustrated that, with further efforts, NIRS has the potential for predicting bacterial numbers and, sequentially, shelf-life of various seafood items.

Fish are perishable. In order to extend shelf-life, fish tend to be stored on ice and such fish are usually sold at lower prices than fresh ones. Therefore, in the pursuit of high profits, some retailers could provide consumers with frozen-thawed (F-T) fish, which usually has inferior quality and high risk in security issues. Moreover, several researchers attempted to differentiate between fresh and frozen-thawed fish by NIRS using PCA, LDA, MLR, and DESIR (dry extract spectroscopy by infrared reflection) (Uddin & Okazaki, 2004; Uddin et al., 2005a). Most recently, the potential of visible (380–1080 nm) and NIR (780–2500 nm) reflectance spectroscopy for authenticating fresh and frozen-thawed swordfish was studied by Fasolato et al. (2012). Compared with the classification results of individual VIS or NIR spectroscopy, VIS-NIRS proved to perform better with an accuracy of over 96.7%. Ottavian et al. (2013) aimed to conduct species-independent discrimination between fresh and frozen-thawed fish by NIRS, and three strategies based on latent variable modeling techniques were proposed to classify the samples. The overall classification rates ranged between 80% and 91%, which demonstrated that VIS/NIRS could be a useful tool to differentiate fresh and F-T fish. Some studies have focused on seafood products, which are among many of the high-value items that are targets of intentional adulteration and economic fraud. Examples include adulteration in crab meat. The widespread availability of blue swimmer crab meat makes it an ideal adulterant for Atlantic blue

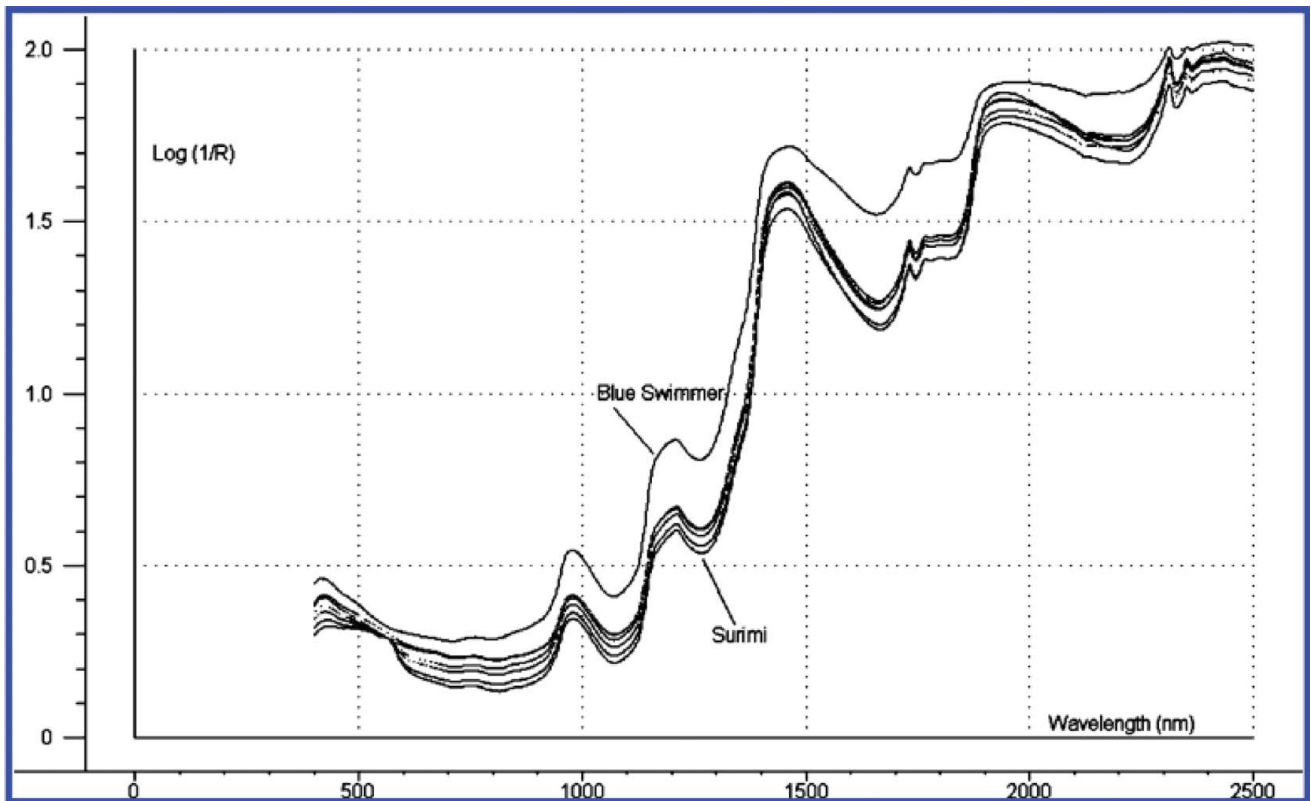


Figure 6 Chart displaying the average absorbance spectra of adulterated samples of blue swimmer crab meat. The top spectrum represents class 0 (0% adulteration), i.e., pure blue swimmer crab meat, while the bottom spectrum represents class 10 (100% adulteration), i.e., pure surimi, and classes 1–9 (10–90% adulteration) are in order from top to bottom (Gayo et al., 2006).

crab meat products, which are more expensive than the former. NIRS was used for authentication as reported by various researchers (Gayo, 2006; Gayo & Hale, 2007). Gayo et al. (2006) used VIS-NIRS (400–2498 nm) to quantify Atlantic blue crab adulterated with blue swimmer crab meat in 10% intervals by building PLS and PCR calibration models. As shown in Fig. 6, the top and the bottom spectra as well as the nine average absorbance spectra between them represent samples with adulterated percentages of 0%, 100%, and 10 to 90%, respectively. The best models by PLS and PCR proved to be excellent for predicting crab meat adulteration with standard errors of prediction (SEP) of 0.252 and 0.244, respectively.

Another issue regarding fish authentication and classification is the separation of bruised samples from normal ones, as bruises represent one of the major causes of fillet downgrading. Application of NIR spectroscopy for detecting bruises and internal defects in fishes was reported by Lin et al. (2003). They tested the ability of visible and SW-NIRS (600–1000 nm) to detect bruises in intact Pacific pink salmon. The images of bruised and nonbruised filleted samples were captured and a PLS model involving six latent variables created good results ($R = 0.83$; $SEP = 0.05\%$). Furthermore, approximately 84% of all nonbruised spectra and 81% of all bruised spectra were correctly classified, respectively.

Fish products are also nutritional and valuable. Therefore, the detection of possible risks inherent in fishery products is another significant area of concern and many studies have been conducted on safety and quality inspection of fish products. Endpoint temperature (EPT) was used to assess previous heat treatment of meat products in order to obtain a preferable lower heating temperature for producing products with optimal sensory qualities and minimal weight loss. Uddin et al. (2005b) aimed to evaluate EPT of kamaboko gel by NIRS and the optimal region turned out to be from 1300 to 1600 nm. PLS and MLR were utilized for building calibration models and good results were acquired ($R = 0.98$). However, fish meal is another source of high-quality proteins with a high price. To prohibit producers from adding meat and bone meals into fishmeal and to identify the source of fish species, appropriate methods are needed to ensure that fishmeal is free of any adulteration or contamination (Cozzolino et al., 2005a). The optimal MPLS quantitative model was developed with a standard error of cross-validation (SECV) of 27.89 g/kg and RPD of 3.37 (Yang et al., 2008).

Fruits and Vegetables

Fruits and vegetables offer essential vitamins and other nutritional components that are important for human health. When it

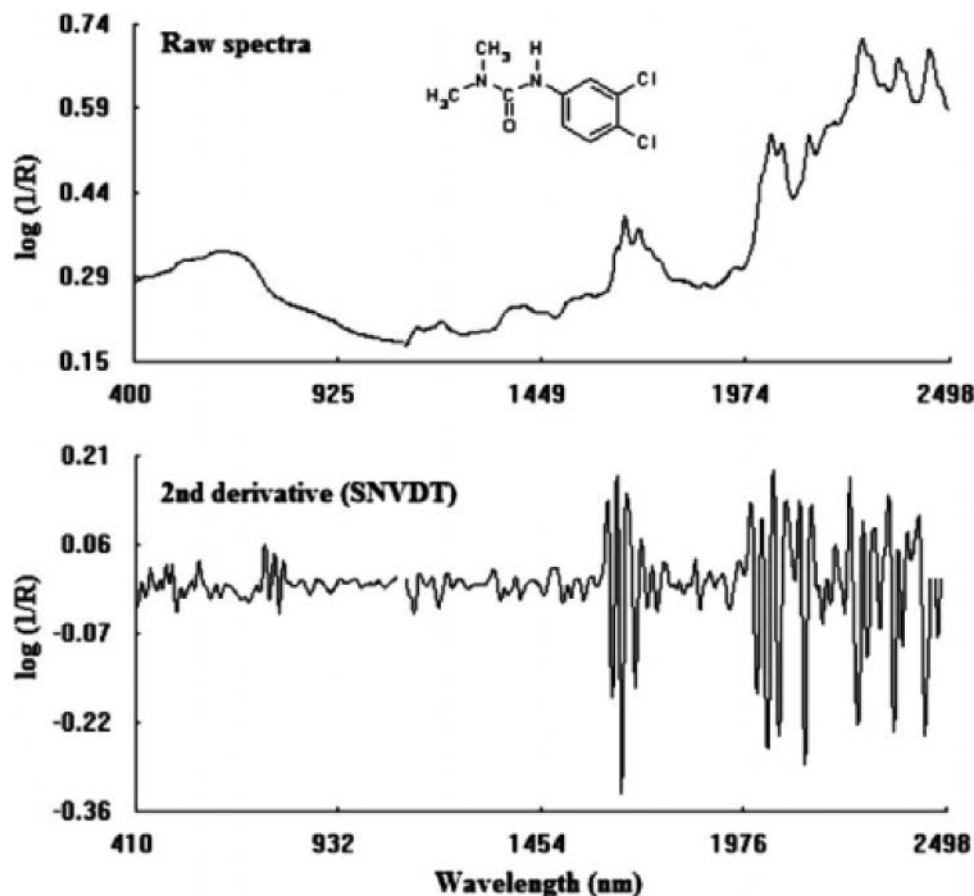


Figure 7 Chart showing NIR spectra for pure diuron samples. A number of strong absorption bands were recorded at wavelengths 2198, 2328, and 2442 nm and medium absorption bands were observed at 1664, 2002, 2040, 2068, and 2136 nm (Salguero-Chaparro et al., 2012).

comes to the safety of fruits and vegetables, pesticide residue is a serious problem to be solved. Recently, there appeared some studies about the application of NIRS for detecting dichlorvos (Xue et al., 2012) and herbicide residues (Salguero-Chaparro et al., 2012) as well as differentiating between conventional and glyphosate-tolerant soybeans (Agelet et al., 2013). In particular, Xue et al. (2012) combined VIS-NIRS (350–1800 nm) with the particle swarm optimization (PSO) algorithm (used for selecting wavelengths of obtained spectral data) and PLSR method to develop calibration models for determination of dichlorvos residue on the surface of navel oranges. The results proved the flexibility of PSO in improving the predictive ability of PLSR models. Besides, the feasibility of NIRS was tested by Salguero-Chaparro et al. (2012) to detect different levels of diuron herbicide residue in intact olives. Figure 7 shows the NIR spectra for pure diuron samples. As is shown, strong absorption bands are recorded at wavelengths 2198, 2328, and 2442 nm and medium absorptions are observed at 1664, 2002, 2040, 2068, and 2136 nm. These wavelength bands were mainly related to fruit color, water molecule absorption, oils, and other fatty substances. The olive samples were categorized into two groups based on diuron concentrations that were above and below the maximum residue limit. PLS-DA was applied accompanied by a

second-order derivative with MSC for discrimination, and the best classification rate was 85.9%.

It is critical to evaluate freshness of fruits and vegetables, which can be measured by shelf-life and, therefore, several studies have been performed based on NIRS technique on pineapples (Di Egidio et al., 2009), green asparagus (Sánchez et al., 2009), and nectarines (Pérez-Marín et al., 2011). Fresh-cut products are defined as any fruits or vegetables that have been physically altered from the original form, but remain in a fresh state (International Fresh-Cut Produce Association; IFPA). In the first study, the shelf-life of fresh-cut pineapple was assessed by FT-NIR in the region of 800 to 2564 nm. The results revealed that the changes occurring in the spectra during storage were mainly connected with water loss and composition modification in the products, probably by enzymatic and microbiologic processes (Di Egidio et al., 2009). Thus, NIRS had the capacity to draw a profile of the products in correlation with the quality changes and predict whether they were still acceptable or not after storage for a certain time. Green asparagus and nectarines were classified on the basis of shelf-life under different storage conditions and irrigation strategies, respectively. Both models were developed by partial least squares 2-discriminant analysis (PLS2-DA). The results

showed that NIRS could be used for monitoring parameter changes of green asparagus and classify samples according to both storage time (81–100%) and postharvest treatment (72–85%). NIRS was also useful for classifying nectarines by storage time (60–80%) and irrigation treatment (63–65%).

As is the case for fruit products, substitution is also a matter of concern for fruits. Thus, an appropriate method for rapid detection and characterization is needed. Kurz et al. (2010) performed quantitative and qualitative analysis to discriminate alcohol-insoluble residue (AIR) and hemicellulose (HC) fractions of apricots, peaches and pumpkins by means of FT-NIR on the basis of cell wall constituents. PCR was applied to create calibration models by correlating spectral data with chemical and gravimetric reference values determined by gas chromatography (GC), and the models proved to be good in prediction. Moreover, they performed classification studies of fruit mixtures, which could effectively reduce the probability of fraudulent blends such as adding peach or pumpkin to apricot, or pumpkin to peach. This study provided a possible way to identify diverse species and origins of fruits for the citrus juice industry.

For the identification of transgenic foods, it is still of great urgency on account that most regions around the world have limited its exploitation and application, especially in Europe. Xie et al. (2007) applied VIS–NIR spectroscopy coupled with PCA, DA, and PLS-DA to classify tomatoes with different genes into transgenic and nontransgenic groups, and PLSR was used for building calibrations. Finally, fairly good results were obtained with R_C of 0.9796, RMSEC of 0.099, R_{CV} of 0.9796, and RMSECV of 0.0993, and this result made it possible to rapidly separate transgenic and nontransgenic foods by NIRS technology.

Edible Oils

In oil safety characterization according to their distinct attributes, NIRS shows its ability in discriminating and classifying edible oils of diverse breeds or grades, detecting harmful substances and other low-quality oil adulterants, as well as differentiating between transgenic and nontransgenic oils. Authentication of virgin olive oils is vitally important to separate them from other oils of lower prices or quality. Marquez et al. (2005) and Sinelli et al. (2010) employed NIRS to characterize and classify virgin olive oils on the basis of fatty acids and their olfactory attributes at the wavelengths of 800 to 2222 nm and 750 to 2500 nm, respectively. In the latter, according to the aroma intensity sensed by the panel, the samples were divided into three grades (“low”, “medium” and “high”) and the obtained spectra by FT-NIR were analyzed by LDA and SIMCA (soft independent modeling of class analogy) and the final prediction rate fell between 71.6% and 100%. In addition, 10 different edible oils were analyzed by FT-NIR combined with LDA for discrimination, achieving 93% accuracy (Yang et al., 2005).

Oil adulteration or mislabeling is a serious problem due to some marketers’ pursuit for extravagant profits, which highly decreases the nutritional and economic values of an oil and may even cause health problems. With regard to adulterant detection in high-priced edible oils, several experiments have been performed to test the feasibility of NIRS in detecting adulteration such as with soybean, olive pomace, corn and peanut oils in camellia oils (400–1700 nm), extra virgin olive oils (833–2500 nm) as well as sesame seed oils (1111–2222 nm) with excellent results (Wang et al., 2006; Mignani et al., 2011; Luo et al., 2012).

Moreover, it must be emphasized that chemical properties of edible oils will change on account of oxidation, polymerization and hydrolysis during the frying process, which affects the quality of oils. NIRS and global PLS were employed for the determination of polymerized triacylglyceride (PTG) in deep-frying vegetable oils, without other foodstuffs being present. PLS models were established on the basis of the obtained spectra and different botanic origins of oils and the prediction errors were 2.28% (w/w) for determining PTG (Kuligowski et al., 2012).

Furthermore, although transgenic plants have many advantages involving strong resistance to insects, weed, disease, and drought along with high yield, some organizations have reservations about their safety and applications. Therefore, reasonable labeling to meet public requirement is essential, and appropriate methods for that are in urgent need. Zhu et al. (2011) and Luna et al. (2013) applied the NIR spectroscopy method to identify transgenic and non-transgenic rapeseed and soybean oils, with encouraging results. For rapeseed oils, by utilizing PCA and PLS-DA, the correct identification rates of nontransgenic and transgenic were 95.56% and 97.30, respectively, and the overall rate was 96.34. For soybean oils, the SVM-DA approach proved to produce better performance than PLS-DA with classification rate of 100% for the training group and 100% and 90% for nontransgenic and transgenic soybean oil samples in the validation group, respectively. Therefore, NIRS is very suitable for the rapid detection of transgenic oil in the future.

Milk and Dairy Products

Milk and dairy products are important sources of high-quality proteins, minerals, and other nutrients. However, the dairy industry is facing a crisis of confidence due to the controversy over its safety in recent years. As a result, many relevant studies by NIRS methods have been performed on raw milk, powdered milk, yogurt (Shao & He, 2009), and more (Woodcock et al., 2008; Wu et al., 2012). Specifically, adulterant addition is the most serious among the issues. Cow milk or milk powder was detected for adulteration with water or whey (Borin et al., 2006; Kasemsumran et al., 2007) and reconstituted milk (Hsieh et al., 2011) by NIRS and appropriate chemometric methods, such as DPLS, SIMCA, LS-SVM and SVM. Also, illegal mixtures added to powdered milk have been

investigated by NIRS, especially melamine, which is a type of nitrogen-rich chemical harmful to human health (Mauer et al., 2009). In particular, Balabin and Smirnov (2011) applied MIR (2500–20,000 nm) and NIR (1110–2500 nm) spectroscopy for melamine detection in liquid milk, infant formula, and milk powder. Feasibility of MIRS and NIRS was evaluated, respectively, along with different analysis approaches containing PLS, orthogonal PLS (O-PLS), polynomial PLS (Poly-PLS), ANN, LS-SVM, and support vector regression (SVR). Results demonstrated that nonlinear regression methods were more effective, and only Poly-PLS was capable of detecting low concentrations of melamine in milk samples, which testified to the ability of MIR/NIRS for safety assessment of dairy products. In addition, VIS/NIR spectroscopy (325–1075 nm) was utilized for separating varieties of yogurt, assisted by BP-ANN with satisfying results of over 96% accuracy rates (He et al., 2006).

Cereals and Cereal Products

It is significant to develop a rapid and efficient method for quality and safety assessment as there are some prohibited transactions of cereals and cereal products containing microbial contaminants and illegal additives as well as some sham and shoddy commodities. Aflatoxin is a mycotoxin produced by *Aspergillus flavus* and *Aspergillus parasiticus*, and it is one of the health-threatening toxins that usually appear in grains under damp conditions. Fernández-Ibañez et al. (2009) and Dachoupakan Sirisomboon et al. (2013) employed NIRS to detect aflatoxin B1 (AFB1) and yellow-green *Aspergillus* contamination in raw grains such as maize, barley, and rice. For maize, the best predictive model to detect AFB1 was obtained by standard normal variate plus detrending correction (SNVD) with $R^2 = 0.80$ and 0.82 and $SECV = 0.211$ and 0.200 for grating and FT-NIRS instruments, respectively. For barley, the best predictive model was developed by SNVD based on dispersive NIRS instrument ($R^2 = 0.85$; $SECV = 0.176$) and by spectral data as $\log 1/R$ for FT-NIRS ($R^2 = 0.84$; $SECV = 0.183$). In terms of rice, the most satisfactory predictive model to detect yellow-green *Aspergillus* was developed by PLSR combined with pretreated NIR spectra (950–1650 nm; $R = 0.437$; $SEP = 18.723\%$; $bias = 4.613\%$), and the results showed the relationship between fungal infection and moisture and starch content. Moreover, NIRS was applied for the determination of sodium hydroxy methane sulfonate mixed into wheat flour (Yuan et al., 2011) and common bread wheat flour in durum wheat adulteration (Cocchi et al., 2006) and both the studies had satisfactory results. It should be emphasized that Cocchi et al. (2006) developed a wavelet-based calibration algorithm, called WILMA. Although WILMA did not improve the predictive models much, it eliminated the need of signal pretreatment and obtained more parsimonious models. Furthermore, Li et al. (2008) examined the ability of VIS-NIRS (325–1075 nm) for the differentiation of paddy seeds with

different storage ages using wavelet, PCA, and ANN for modeling. The model yielded a promising result of 97.5% accuracy. In 2011, NIR (1100–2500 nm) was coupled with PLS and LS-SVM to predict starch and protein in rice after different irradiation. The established models proved to be best for starch prediction using the NIR region, and the MIR region for protein (Shao et al., 2011).

Others

In addition to the abovementioned applications of NIRS in safety assessment involving meat, fish, dairy, cereals, and fruits and vegetables, recent studies have demonstrated its suitability in other foodstuff. For example, efforts have been made to identify frauds involving coffee (Ebrahimi-Najafabadi et al., 2012), honey (Zhu et al., 2010), red wine (Ferrari et al., 2011), vinegars (Liu et al., 2011; Bao et al., 2014), spirulina powder (Wu et al., 2011), and others. Ebrahimi-Najafabadi et al. (2012) blended nine different types of coffee with four types of barley at different roasting degrees and NIRS (1000–2500 nm) coupled with PLS as well as a genetic algorithm (GA) was introduced to establish models in order to quantify the barley in the tested samples. Results were excellent with RMSE of 1.4% w/w and 0.8% w/w for the test set and an external set, respectively. As a type of natural and nutritional sweet energy substance, honey is often adulterated with other low-priced sweeteners. Some researchers have already implemented several experiments on the basis of NIRS. Mishra et al. (2010), Chen et al. (2011a) and Zhu et al. (2010) used NIRS to detect jaggery syrup, high-fructose corn syrup, and other sweet adulterants in honey samples. The accuracy rates were 0.90, 0.90, and 0.95 by means of PCA and PLS, DPLS as well as LS-SVM and BP-ANN, respectively. These studies demonstrated that NIRS combined with appropriate chemometric methods could be used as a nondestructive method to determine adulteration in honey.

Furthermore, to suppress and avoid pseudotransactions, distilled alcoholic beverages, roasted coffee, instant noodles, milk teas, and Chinese lotus root powder were investigated for variety discrimination and classification by NIRS along with chemometric methods including PCA, SIMCA, PLS, OWAVEC (orthogonal wavelet correction), BPNN, LS-SVM, and proposed partial least squares class model (PLSCM) (Pontes et al., 2006; Pizarro et al., 2007; Liu & He, 2008; Liu et al., 2009; Xu et al., 2013). In addition, to prohibit fraudulent incidents, NIRS can be applied to conduct qualitative and quantitative analysis of hazardous substances in foodstuffs. For instance, the irradiation doses of irradiated sucrose were measured by VIS-NIRS along with PCA (Gong et al., 2012).

Fumonisin B₁ and B₂ and melamine contents are frequently discovered in contaminated corn or intentionally adulterated soybean meal. Most recently, corn meal and soya bean meal were also examined for fumonisins B₁ and B₂ and melamine contents by FT-NIR and near-infrared reflectance

spectroscopy. The obtained results were satisfactory with correlation coefficients of 0.964 and 0.89 to 0.99 and root mean square error of 0.630 and 0.081 to 0.276% for corn meal (Gasparido et al., 2012) and soybean meal, respectively (Haughey et al., 2013).

Furthermore, NIRS coupled with other instruments have also been studied. For example, electronic-nose (E-nose), originated from many types of aroma-sensor technologies, has been developed for plenty of applications in the food industry, and most recently, E-nose was combined with NIRS and computer vision (CV) for measurement of TVB-N in pork meat (Huang et al., 2014). Results showed that integrating NIRS, CV, and E-nose technique could significantly improve the prediction performance of TVB-N content, which implied the possibility of the integration of NIRS with E-nose.

CONCLUSIONS AND FUTURE OUTLOOK

Recent advances in food safety evaluation by NIRS technique are presented and discussed and it can be confirmed that this technique has the potential for assessing food safety properties, detecting adulterants, as well as performing characterization and classification of foods mainly related to meat, fish and fish products, edible oils, milk and dairy products, cereals, and fruits and vegetables. As for controlling safety attributes, NIRS provides more information compared with conventional approaches in determining microbial contamination and shelf-life of food, detecting pesticide residues or toxic substances produced during processes, along with harmful fraudulent materials mixed into food products. In addition, NIRS shows to be feasible in the identification of adulteration, and also major fraudulent incidents of blending high-priced commodities with those of low-quality, low price, and low nutritional values. Moreover, NIRS can be used for the differentiation of various species and classification according to different origins or processing techniques which may be prohibited as adulterants. Therefore, NIRS combined with appropriate chemometric methods should be required for assessing technological and sensory characteristics in the food field. However, NIRS has limited capacity for estimating heterogeneous samples such as fish, meat, fruits, and vegetables. Besides, low precision and subjectivity of the reference methods are also constraint in its widespread applications. Consequently, more robust calibrations are needed with regard to better sampling procedures and improvement of reference methods.

Hyperspectral imaging, the combination of spectroscopy and imaging methods, is a novel nondestructive emerging technique used for food safety control. This technique can not only examine the chemical constituents of the tested samples but also visualize the distribution of the components and locate the positions of specific spots. Technically, both the techniques are based on a model establishment by chemometric methods. Therefore, better efforts should be devoted to introduce more

effective algorithms, develop more robust models and try to decrease errors.

Overall, NIRS is quite promising in food safety assessments and will play an essential role in safety inspection in the food industry. Still, more research is needed to investigate its full power.

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