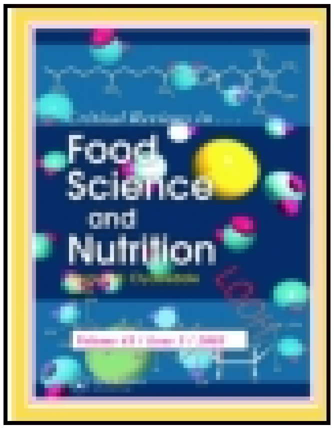

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Applications of Emerging Imaging Techniques for Meat Quality and Safety Detection and Evaluation: A Review

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Applications of Emerging Imaging Techniques for Meat Quality and Safety Detection and Evaluation: A Review

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Abstract: With the improvement of people's living standard, many people nowadays pay more attention to meat quality and safety. However, traditional methods for meat quality and safety detection and evaluation, such as manual inspection, mechanical methods and chemical methods, are tedious, time-consuming, and destructive, which cannot meet the requirements of the modern meat industry. Therefore, seeking out rapid, nondestructive and accurate inspection techniques is important for the meat industry. In recent years, a number of novel and noninvasive imaging techniques, such as optical imaging, ultrasound imaging, tomographic imaging, thermal imaging, and odor imaging, have emerged and shown great potential in quality and safety assessment. In this paper, a detailed overview of advanced applications of these emerging imaging techniques for quality and safety assessment of different types of meat (pork, beef, lamb, chicken, and fish) is presented. In addition, advantages and disadvantages of each imaging technique are also summarized. Finally, future trends for these emerging imaging techniques are discussed, including integration of multiple imaging techniques, cost reduction, and developing powerful image-processing algorithms.

Keywords: Pork; beef; lamb; chicken; fish; nondestructive; optical imaging; ultrasound imaging; tomographic imaging; thermal imaging.

1 Introduction

Meat is a nutritious and popular food commodity as it can provide high-quality proteins, vitamins, minerals, and some other nutrients to sustain and improve human health. In people's daily life, meat and meat products are always regarded as the main source of animal protein. With the recent development of social economies and the improvement of human's living standards, people nowadays pay more attention to meat quality and safety. In order to meet the higher requirements of consumers and keep competitive in the market, the modern meat industry needs to produce not only higher-quality products but also safer products. Generally, meat quality and safety are affected by a variety of external/internal factors. For example, the variation of meat composition (mainly protein, moisture, and fat) could cause variations in the biochemical properties of meat, such as color, juiciness, and surface texture. In addition, a series of processing methods, such as electrical stimulation and freezing, could also influence meat quality. For quality and safety evaluation, manual inspection is a traditional method, carried out by some experienced inspectors. Although the experienced inspectors can ensure that the occurrence of misclassifications is rare, this manual method is subjective, time-consuming, and thus not suitable for on/in-line monitoring. Besides manual inspection, mechanical measurement and chemical methods are also traditionally used for meat quality and safety evaluation. Compared with the manual method, mechanical measurement and chemical detection can provide objective results. However, these two objective methods are destructive, laborious, and require lengthy sample preparation (Xiong et al., 2014a). To overcome the shortcomings of traditional methods and satisfy the requirements of the modern meat industry, it is significant to develop some nondestructive, accurate, and rapid techniques for assessing meat quality and safety.

Nondestructive testing is defined as that a meat sample could be assessed or examined without changing it in any way so that the influence of condition-changing can be determined (Valous et al., 2010). During the last 2 decades, a number of nondestructive methods, particularly for imaging techniques and spectroscopy, have achieved great success in meat quality and safety assessments (ElMasry et al., 2012a). Imaging techniques have the biggest advantage of providing abundant spatial information while spectroscopy can provide abundant spectral information. Either spectral information or spatial information may relate to sensory, chemical, and physical properties of meat. Through processing and analyzing these spectral or image features, the quality of meat surfaces and quality factors that cannot be detected by human inspectors, such as structural and textural features can be objectively assessed. More recently, with the rapid development of computer hardware and image processing algorithms, some novel imaging techniques have emerged and are already well developed, such as ultrasonic imaging, tomographic imaging (X-ray imaging and magnetic resonance imaging), optical imaging (fluorescence imaging, Raman imaging, and hyperspectral imaging), odor imaging, and thermal imaging.

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Ultrasound imaging is a cost-effective, easy, and reliable technology, which can acquire internal images for meat quality and safety assessment. Usually, there are 2 modes for ultrasonic imaging: A-mode (amplitude modulation) and B-mode (brightness modulation). The B-mode is more widely used (Ribeiro et al., 2008; Fukuda et al., 2013). Besides ultrasound imaging, tomographic imaging is also an efficient tool for meat quality and safety evaluation, which can be specifically separated into X-ray imaging and magnetic resonance imaging. X-ray imaging, especially for X-ray computed tomography, utilizes X-rays for creating tomographic images of scanned samples. When the tissues in the tested sample attenuate X-rays, a thin cross-sectional image of the sample can then be obtained. By stacking and reconstructing several thin cross-sectional images, three-dimensional visualization of the internal characteristics of the sample can be achieved (Macfarlane et al., 2006; Navajas et al., 2007). Compared with X-ray computed tomography, magnetic resonance imaging makes use of different characteristics in the electromagnetic spectrum for assessing meat quality and safety because different biochemical properties in the tested objects can lead to different absorption and emission of energy in the electromagnetic spectrum (Hansen et al., 2008; Damez et al., 2012, 2013). On the other hand, optical sensing techniques, including fluorescence imaging and hyperspectral imaging, have been demonstrated as promising tools for meat quality and safety assessment. The principle of fluorescence imaging is to utilize the luminescence emitted by tested objects for imaging (Cho et al., 2009; Burfoot et al., 2011). However, conventional fluorescence imaging has certain

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limitations in meat quality and safety assessment. To solve this problem, researchers attempted to integrate fluorescence imaging with other imaging tools, such as microscopy imaging and hyperspectral imaging, and good results were obtained with meat quality and safety evaluation. In terms of hyperspectral imaging, it integrates the merits of computer vision and conventional spectroscopic techniques so that both spectral information and spatial information can be provided simultaneously (Tao et al., 2012a; Barbin et al., 2012a, b). After processing and analysis of these data, either external or internal traits in meat could be well predicted. Traditionally, a hyperspectral imaging system is made up of 4 essential components: a high-performance camera, a spectrograph, an illumination unit, and a computer equipped with image acquisition software (Xiong et al., 2014b). Currently, applications of hyperspectral imaging are mostly focused on spectral information without using spatial information, which also plays an important role in meat quality inspection, especially when predicting external traits. Accordingly, to exploit the potential of hyperspectral imaging, some researchers (Zhu et al., 2013; He et al., 2014; Liu et al., 2014a) have attempted to dig out useful spatial information from hyperspectral images for meat quality and safety evaluation, and the results of their studies were encouraging. Finally, thermal imaging, a further recent imaging technique, utilizes infrared radiation emitted by a body surface for producing thermal images, which shows the temperature distribution of the object (Costa et al., 2010; Weschenfelder et al., 2013).

In a previous review, Du and Sun (2004) summarized recent developments in image-processing techniques for food quality evaluation. In this study, a majority of image processing methods for image acquisition, image segmentation, and feature extraction were presented in details. In another study, Liang et al. (2011) summarized imaging technologies used for inspecting the quality of fish and fish products, including visible/near-infrared light imaging, visible/near-infrared spectral imaging, computed tomography, and magnetic resonance imaging. Complementary to the reviews above, this paper provides a detailed overview in advanced applications of emerging imaging techniques for the quality and safety evaluations of various types of meat (beef, pork, lamb, chicken, and fish). In addition, the technical limitations and future trends for these emerging imaging techniques are also discussed.

2 Emerging imaging techniques based on mechanical waves

As shown in Table 1, there are different types of emerging imaging techniques that can be applied for meat quality and safety detection and evaluation. These techniques have been developed based on different principles such as mechanical and electromagnetic waves. Mechanical waves are produced by mechanical vibration and usually include transverse waves and longitudinal waves. Different from electromagnetic waves, mechanical waves cannot be spread in vacuum, and their propagation requires specific media. Water wave, acoustic wave, and seismic wave are common mechanical waves. Ultrasound imaging is a widely used technique which utilizes the acoustic characteristics of tested objects for imaging, and its recent

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applications are shown in the following sections.

2.1 Ultrasound imaging

Most of the applications of ultrasound imaging so far were concentrated on predicting body composition of live animals, including intramuscular fat (IMF) percentages, lean content, and fat tissue thickness (Hassen et al., 2001; Newcom et al., 2002; Youssao et al., 2002; Ribeiro et al., 2008; Harron and Dony, 2009; Ayuso et al., 2013; Fukuda et al., 2013). Ayuso et al. (2013) investigated the potential of ultrasound imaging for predicting IMF percentages of Iberian pigs. In this study, ultrasound images were first acquired from 241 Iberian pigs and a predictive model was built using a stepwise regression algorithm, but the final results were not quite satisfactory with a low correlation coefficient (R) of 0.47. In order to improve the accuracy of IMF prediction, Fukuda et al. (2013) developed an image recognition method based on independent component analysis (ICA) and neural networks. After image acquisition, texture features in the ultrasound images were extracted. Then, ICA was used to compress the texture data. Finally, the IMF percentage was predicted using a neural network, and a higher R of 0.70 was given, suggesting that the ICA-based method was effective to improve the accuracy.

On the other hand, ultrasound imaging coupled with other imaging tools such as computer vision has also been applied to determine meat quality. For example, Fortin et al. (2003) integrated ultrasound imaging with video imaging for quality classification of pork carcasses. In this study, the role of ultrasound imaging was to scan a cross-section of the loin muscle while video imaging was used to capture two-dimensional and three-dimensional images of the carcass. A predictive model was established for estimating salable meat yield, and good results were shown with high R^2 of 0.82 and low residual standard deviation (RSD) of 1.68.

In terms of meat safety detection, ultrasound imaging can be used as a promising tool (Cho and Irudayaraj, 2003; Pallav et al., 2009). As we know, foreign objects, such as bone fragments, glass, or metal matter in meat and meat products, could do harm to people's health. Based on the different acoustic impedances between foreign objects and meat, ultrasound imaging can accurately distinguish foreign objects of a meat surface. For example, Cho and Irudayaraj (2003) applied a new noncontact air instability compensation ultrasound imaging technique for detecting foreign objects in chicken meat. Ultrasound images of boneless chicken breast with foreign materials (metal and glass fragments) were first acquired, and then a quantitative analysis of ultrasound parameters was performed. The final results were encouraging, demonstrating that ultrasound imaging could be an effective tool for detecting the presence of foreign objects in meat products.

3 Emerging imaging techniques based on electromagnetic waves

According to the frequency from low to high, electromagnetic radiation can be classified into microwave, infrared, visible light, ultraviolet rays, X-rays, and gamma rays. Compared with mechanical waves, electromagnetic waves do not require a medium to propagate, and all kinds of electromagnetic waves can be spread in vacuum. X-ray imaging, magnetic resonance imaging, fluorescence imaging, and hyperspectral imaging techniques are all based on electromagnetic waves for imaging.

3.1 X-ray imaging

Considering health issues, consumers usually prefer to buy lean meat with a minimal fat content. To satisfy the expectation of consumers, the modern meat industry needs to determine carcass composition. X-ray imaging, particularly for computed tomography, has been widely used for predicting carcass composition (Romvári et al., 2006; Karamichou et al., 2006; Macfarlane et al., 2006; Navajas et al., 2007; Font i Furnols et al., 2009; Vester-Christensen et al., 2009; Picouet et al., 2010; Prieto et al., 2010; Jensen et al., 2011). Prieto et al. (2010) applied spiral computed tomography for predicting beef composition, including subcutaneous fat, intermuscular fat, total fat, and muscle content. In this study, 194 animals from two cattle breeds were used for investigation. After image acquisition and data processing, predictive models were established using a multivariate calibration method, namely, partial least square regression (PLSR), and acceptable results were obtained with high accuracy for predicting the subcutaneous fat (R^2, RMSECV = 0.94, 34.60 g and 0.92, 34.46 g), intermuscular fat (R^2, RMSECV = 0.81, 161.54 g and 0.86, 42.16 g), total fat (R^2, RMSECV = 0.89, 65.96 g and 0.93, 48.35 g), and muscle content (R^2, RMSECV = 0.99, 58.55 g and 0.97, 57.45 g) in 2 sets of meat samples, respectively. Besides, the compositions of other meat species, such as pork (Font i Furnols et al., 2009) and lamb (Navajas et al., 2007), have also been well predicted using computed tomography.

Salt distributional analysis in salted meat products by the use of X-ray computed tomography was also a major application (Håseth et al., 2008; Vestergaard et al., 2004; Korver et al., 2004; Segtnan et al., 2009). Salted and smoked meat products are popular commodities worldwide, however the content of salt concentration has an apprent effect on human health. Therefore, consumers pay much attention to salt concentration in meat products before making a buying decision. Segtnan et al. (2009) demonstrated that X-ray computed tomography can be a rapid and nondestructive technique for monitoring the variation of NaCl content in salted salmon fillets. In their study, the best results were obtained by combining 3 X-ray voltages (80, 110, and 130 kV), which gave a low prediction error of 0.40% and a high R of 0.92.

Similar to ultrasound imaging, X-ray imaging can also be used to detect foreign objects in meat products (Tao and Ibarra, 2000; Tao et al., 2001; Mery et al., 2011). Tao and Ibarra (2000) investigated the potential of X-ray imaging for detecting bone fragments in chicken fillets, but the final results were unsatisfactory. To improve the prediction accuracy, Tao et al. (2001) later developed a new image segmentation method, namely adaptive thresholding. More recently, Mery et al. (2011) applied an X-ray machine vision method for fish bone detection, which

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showed good results with a detection accuracy of 99%. Although X-ray imaging has obtained a broad range of applications, there are some shortcomings in the X-ray imaging technique. For example, X-ray imaging cannot detect all kinds of foreign objects. Objects like hair, paper, and plastics cannot be easily recognized using the X-ray imaging technique as their densities are similar to that of water.

3.2 Magnetic resonance imaging

In recent years, magnetic resonance imaging has been demonstrated as a promising technique for monitoring quality changes in various foods, such as fruit (Clark and MacFall, 2003; Galed et al., 2004; Shaarani et al., 2010), cereals (MacMillan et al., 2008), and meat (Cernadas et al., 2005; Hansen et al., 2008; Damez et al., 2012). Particularly, applications of magnetic resonance imaging for meat quality and safety detection and evaluation can be concluded in the following 4 aspects.

First, magnetic resonance imaging has been widely used for measuring the content of body compositions and visualizing their distribution in meat and meat products (Collewet et al., 2005; Mohrmann et al., 2006; Monziols et al., 2006; Davenel et al., 2012; Kremer et al., 2013). For example, Collewet et al. (2005) developed a 1.5T magnetic resonance imaging system for the nondestructive measurement of the lean meat percentage in pig carcasses. The contrast between muscle and fat tissues was first optimized by choosing the proper acquisition protocol. Then,

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image segmentation was used for image analysis. Finally, automatic image segementation achieved good performance in predicting the volume of muscle with an estimation error of 1.10% for lean meat percentage. In another study (Brix et al., 2009), a novel method, chemical shift-based magnetic resonance imaging and gas chromatography (GC), was proposed to predict the content of fat and visualize its distribution in Atlantic mackerel. Fish in 2 different body condition stages (most starved and well fed) were used in the investigation. For starved fish, fat content (40 ± 23 mg/g) measured by magnetic resonance imaging had a correlation with that measured by GC (39 ± 16 mg/g). However for well fed fish, prediction results showed no agreements (447 ± 101 by magnetic resonance imaging; 212 ± 89 by GC). The reason might be that non-triglyceride lipids could have been produced in the well-fed fish, and the 2 analytical methods had different sensitivity to these lipids. The above studies showed that magnetic resonance imaging could predict fat content more accurately compared with traditional analytical methods, and magnetic resonance imaging has the ability to achieve visualization of fat distribution. Besides pork and fish, composition of beef and other types of meat have also been well predicted using magnetic resonance imaging (Ballerini et al., 2002; Toussaint et al., 2005).

Second, magnetic resonance imaging is capable of monitoring salt diffusion and water mobility in meat during brine curing (Aaslyng et al., 2003; Ruiz-Cabrera et al., 2004; Vestergaard et al., 2005; Vestergaard et al., 2005; Hansen et al., 2008; Veliyulin et al., 2009; Bouhrara et al., 2011; Bouhrara et al., 2012a, b). Hansen et al. (2008) applied ^{1}H and ^{23}Na

magnetic resonance imaging for monitoring the diffusion of NaCl in meat. The results suggested that microstructure, especially for the transverse structures, was greatly changed in the meat during curing. In addition, the diffusion coefficient increased during curing, and the diffusion behavior in different regions of meat was obviously different. For example, the diffusion process in meat with connective tissue/fat was different from that with pure myofilament tissue. The barrier effect of fat content was demonstrated by Veliyulin et al. (2009) through analysis of fat distribution using ^{1}H magnetic resonance imaging and imaging salt distribution using ^{23}Na magnetic resonance imaging. On the other hand, ^{1}H and ^{23}Na magnetic resonance imaging were also applied for the control and optimization of brining in fish products (Erikson et al., 2004; Aursand et al., 2008; Aursand et al., 2010). The results of these studies suggested that the higher the density of the raw material structure, the lower the salt diffusion.

Third, monitoring the cooking process by the use of magnetic resonance imaging is another important application (Shaarani et al., 2006; Bouhrara et al., 2011; Bouhrara et al., 2012). During cooking, structural and physical qualities would change, leading to the variation of sensory, nutritional, and technological characteristics in meat products. Bouhrara et al. (2011) proposed an approach based on dynamic magnetic resonance imaging and thermal simulation to monitor deformations and water transfer in meat. The observations in this study were similar to results reported in the literature using destructive methods. In order to obtain better understanding of the variations of deformation and temperature in meat muscle during cooking, Bouhrara et al. (2012)

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developed an optimized nonlinear image registration technique for measuring deformations. Figure 1 presents several representative simulated temperature maps and magnetic resonance images, which can reflect the variation of deformation fields inside the muscle (in direction and magnitude) during heating. Only 3 representative maps with average temperatures of 47.5 °C, 57 °C, and 68.3 °C are shown because the deformation outside the range (44 °C to 70 °C) was negligible. The results indicated that deformation increased with temperature in several phases whose characteristics depended on the muscle composition.

Finally, magnetic resonance imaging could provide structural information on muscle tissue in several ways (Monziols et al., 2006; Pérez-Palacios et al., 2011; Damez et al., 2012). One way is to utilize diffusion tensor imaging (DTI), which is conducted by measuring diffusion coefficients in at least 6 directions. Damez et al. (2012) used DTI at different degrees of diffusion sensitization to acquire intra-voxel structural information, including fiber type and diameter. Promising results were obtained, suggesting that structural details correlated with metabolic characteristics. In addition, Pérez-Palacios et al. (2011) integrated magnetic resonance images with computational muscle-driven texture feature analysis for automatic recognization of the feeding background of the Iberian pigs, and the final results were encouraging. Another feasible method for studying muscle structure is to utilize susceptibility-weighted images because connective tissue in muscle has contrasted magnetic susceptibility (Laurent et al., 2000; Bonny et al., 2001a).

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3.3 Fluorescence imaging

Fluorescence is a form of luminescence, and fluorescence imaging makes use of the fact that objects, having absorbed light or other electromagnetic radiation, can emit fluorescence. Discrimination of contaminants in meat is of prime importance in the meat industry, especially for those contaminants that are not easily recognized using human vision. Fluorescence imaging is superior for detecting animal feces (Kim et al., 2003; Cho et al., 2009; Burfoot et al., 2011). Cho et al. (2009) developed a laser-induced fluorescence imaging system for the discrimination of feces-contaminated poultry carcasses. In their study, fluorescence emission images at 630 nm were first acquired, and then two image processing algorithms, threshold and image erosion, were both used to identify fecal spots. The final detection accuracy for fecal matter was 96.6%. For other meat species, Kim et al. (2003) developed a multispectral laser-induced fluorescence imaging system for detecting fecal matters in pork, and Burfoot et al. (2011) classified contaminated beef and lamb carcasses using fluorescence imaging.

Conventional fluorescence imaging has certain limitations in meat quality and safety assessment because not all materials can be excited to fluoresce. Therefore, fluorescence imaging coupled with the other noninvasive tools, such as multispectral/hyperspectral imaging and laser confocal scanning microscopy (LCSM), was more widely used for predicting quality traits in meat. For example, Skjervold et al. (2003) combined autofluorescence with multispectral imaging to distinguish 3 different structural components (myofiber, fat, and connective tissue) in meat. The final results showed that the combinations of excitation and emission wavelengths (290/332 nm for myofiber, 322/440 or 322/405 nm for fat, and 380/440 nm for connective tissue) achieved the best performance for discriminating the 3 components. In addition, Adedeji et al. (2011) integrated fluorescence imaging with LCSM for visualizing fat distribution in deep-fat-fried chicken-nugget batter. Images were acquired at 2 different modes of the microscope: fluorescence and reflection. Through image analysis, the variation process of fat distribution, which was affected by frying time, temperature, and product depth, could be presented.

3.4 Hyperspectral imaging

As hyperspectral imaging integrates the merits of computer vision and conventional spectroscopy, abundant spatial and spectral information can be simultaneously obtained from hyperspectral images. In recent years, hyperspectral imaging has been widely used for food quality evaluation and safety detection (Mehl et al., 2004; Gowen et al., 2009; Singh et al., 2009). In particular for meat, considerable research endeavors have been conducted to evaluate their quality and safety indicators (Chao et al., 2010; Tao et al., 2010; Yang et al., 2010; Peng et al., 2011; Costa et al., 2011; ElMasry et al., 2012b; Sone et al., 2012; He et al., 2012; Wu et al., 2012b; Tao et al., 2012a, 2012b; Kamruzzaman et al., 2012a; Kamruzzaman et al., 2012b; Barbin

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et al., 2012a; Barbin et al., 2013a, 2013b, 2013c, 2013d; Elmasry et al., 2013; Kamruzzaman et al., 2013; Feng and Sun, 2013a; Feng and Sun, 2013b; Dai et al., 2014; Wu et al. 2014). In order to clearly illustrate the development of hyperspectral imaging, several developmental stages have been concluded, which are explained in the following sections.

The first stage was to extract spectral information in hyperspectral images for predicting quality traits of meat (Lawrence et al., 2003; Wold et al., 2006; Cluff et al., 2008). Encouraging results of these studies demonstrated that hyperspectral imaging could be a smart and accurate tool for meat quality and safety evaluation and detection. Although spatial information in hyperspectral images is also important, especially when external traits were detected, spatial information has not been fully exploited in these applications. Therefore, to make good use of spatial information in hyperspectral images, many research studies have been conducted.

The second stage was to dig out image features from hyperspectral images for modeling. To extract image features, some algorithms should be used, such as the gray-level co-occurrence matrix (GLCM), grey-level-gradient co-occurrence matrix (GLGCM), and wavelet transform (WT) (Qiao et al., 2007a; Naganathan et al., 2008a, b; Qin et al., 2009; Kamruzzaman et al., 2013). Among the 3 algorithms, GLCM is the most widely used one, and the principle of GLCM is to utilize some statistical approaches from the co-occurrence matrix, $P_{d,\theta}$ with the grey value i and j for extracting texture features (Haralick et a., 1973). Before building the matrix, distance between the pixel pairs (d) and the direction of the pixel pairs (θ) must be chosen, and the direction θ is usually selected from 4 different orientations at 0°, 45°, 90°, and 135°. Kamruzzaman et al. (2013) attempted to achieve tenderness categorization using textural features. In this study, GLCM was first applied to extract 4 textural parameters (contrast, correlation, energy, and homogeneity) from hyperspectral images at 11 tenderness-related wavelengths. Then, textural variables were used to build new models. Although the models gave unsatisfactory results with a low R of 0.52, the outcome of this study was quite important for future research.

The third stage was to integrate spectral data with image features for modeling (Huang et al., 2013; Zhu et al., 2013; He et al., 2014; Liu et al., 2014a). In terms of quality classification, Zhu et al. (2013) applied visible and near-infrared hyperspectral imaging to differentiate between fresh and frozen-thawed (F-T) fish fillets, and the flowchart of data processing is shown in Figure 2. Principal component analysis (PCA) was first used for dimension reduction on the region-of-interest (ROI) image, and it was found that the first 3 principal components (PCs) could explain over 98% of variances of all spectral bands. Then, GLCM was implemented on the 3 (PC) images to extract 36 textural feature variables in total. Least squares-support vector machine (LS-SVM) classification models were finally developed to differentiate between fresh and F-T fish based on spectral and textural variables. Satisfactory average correct classification rate of 97.22% for the prediction samples was achieved. In terms of predicting quality traits, He et al. (2014) achieved a good performance in tenderness prediction of salmon fillets by fusing spectral information and textural features. In this study, 3 textural parameters (contrast, homogeneity, and energy) were extracted from the hyperspectral images only at 4 wavelengths selected by the GLCM method, and 12 textural variables were then obtained. Based on the spectral and textural data (12 textural variables and 4 wavelength variables), a new LS-SVM model was built, and satisfactory results were obtained with a high R_p of 0.892 and a low RMSEP of 1.172, suggesting that spectral information coupled with textural features were more suitable for tenderness prediction of salmon fillets.

In addition, some researchers attempted to apply hyperspectral imaging for monitoring quality variations during meat processing (Kandpal et al., 2013; Liu et al., 2014b). In this study (Liu et al., 2013), hyperspectral images (400-1000 nm) of pork slices were first acquired at different periods of the salting process. Then, PLSR was used to build calibration models based on full wavelengths, and good results were given with R^2_p of 0.928 and 0.909 for NaCl content and water activity (a_w), respectively. Based on optimal wavelengths selected using regression coefficients (RC), new models were established using 3 linear calibration algorithms, including PLSR, principal component regression (PCR), and multiple linear regression (MLR). The MLR models achieved the best performance with R^2_p of 0.930 and 0.914, and RMSEP of 0.682 and 0.007 for NaCl content and a_w, respectively. Finally, image visualization of NaCl content was realized by transferring the MLR model to each pixel in the image with a developed algorithm. The encouraging results demonstrated that hyperspectral imaging had the potential for monitoring quality variation during salting in the meat industry.

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4 Emerging imaging techniques based on heat flow and colorimeter sensor array

Besides utilizing mechanical waves and electromagnetic waves for imaging, thermal imaging utilizes temperature and heat flow for producing thermal images, while odor imaging makes use of a colorimeter sensor array for detecting non-visible matters.

4.1 Thermal imaging

Thermal imaging is a rapid, noninvasive, and accurate technique, which can catch moving targets in real time and create a visual picture, showing temperature differences over a large range. Due to these merits, thermal imaging has been widely used for meat safety assurance and quality monitoring.

On one hand, thermal imaging has been used to assess meat quality (Lawrence et al., 2010; Costa et al., 2010; Weschenfelder et al., 2013). For example, Costa et al. (2010) applied infrared thermography to evaluate pork and ham quality on a slaughter line. Forty hams obtained from pig carcasses were first thermographed, and through analysis of surface temperature differences, ham quality could be evaluated. The final results showed that hams with a lower fat cover displayed obvious differences in average surface temperature, and infrared thermography could be used as a practical and noninvasive tool for achieving quality classification of hams.

On the other hand, thermal imaging has also been used to determine diseases in animals

(Schaefer et al., 2004; Schaefer et al., 2012). For example, Schaefer et al. (2012) investigated the potential of infrared thermal imaging to determine bovine respiratory disease complex (BRD) in cattle. The final results demonstrated that true positive animals for BRD based on a gold standard including core temperature, clinical score, white blood cell number, and neutrophil/lymphocyte ratio displayed higher peak infrared thermal values of 35.5 ± 0.35 ^{o}C compared to that of 34.9 ± 0.22 ^{o}C for true negative animals.

As most of the applications of thermal imaging are still in the experimental stages, further research should be focused on facilitating the industrial adoption of this technique. To achieve industrial application, it is necessary to solve some technical challenges in the future. For example, the cost of a thermal imaging system is still high, which has been the biggest barrier for industrial applications. In addition, thermal interference from the ambient environment is also a great challenge to the development of thermal imaging sensors on an industrial scale.

4.2 Odor imaging

Odor imaging is a novel, sensitive, and convenient technique, which has good capability to evaluate meat freshness (Huang et al., 2011; Feiyan, 2011; Salinas et al., 2012). For example, Huang et al. (2011) developed an olfaction system based on a colorimetric sensor array for the evaluation of fish freshness. In this study, 9 chemically responsible dyes were selected for the colorimetric sensor array. The digital data representing the color change profiles for the fish

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samples were analyzed using PCA. Finally, the chub samples were classified into 3 freshness groups using a radial basis function neural network, with an overall classification accuracy of 87.5%. In another study, Salinas et al. (2012) attempted to monitor chicken meat by means of a colorimetric sensor array. Multivariate algorithms, PCA and PLSR, were used to process the chromogenic array data. The results of PCA analysis showed that 9 chemically responsible dyes could explain 95% of variance. Finally, a PLSR model was built to correlate the chromogenic data with the ageing of chicken meat and perfect prediction results were given with a high R of 0.994.

In terms of meat safety, Salinas et al. (2014) monitored microorganism spoilage of fresh pork sausages using a colorimetric sensor array. PLSR models were built to predict values of the storage days, mesophilic bacteria, and the sensory score. Satisfactory results were acquired with R of 0.9300, 0.9472, and 0.9381, respectively. Although odor imaging has apparent advantages, there are still some limitations. For example, its application scope is narrow because only odorous products can be inspected by the odor imaging technique. Besides, the selection of responsive dyes is also a technical challenge for applications.

5 Future trends

Recent applications of emerging imaging techniques for meat quality and safety assessment are summarized in Table 1. As shown in Table 1, most of the emerging imaging techniques were

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used in specific applications due to their limitations and disadvantages. To broaden their application scope, technical challenges existing in each imaging technique should be solved. First, integration of multiple imaging techniques would be promising. For example, conventional fluorescence imaging has certain limitations in the analysis of meat quality and safety because not all materials can be excited to fluoresce. However, integration fluorescence imaging with other imaging tools, such as microscopy imaging and hyperspectral imaging, has achieved better performances in detecting quality traits in meat. In addition, it is also promising to integrate imaging techniques with other non-destructive tools, such as Raman spectroscopy and electronic nose. Second, most of the emerging imaging techniques, except the odor imaging technique, have the potential for achieving on-line inspection in the meat industry. In recent years, with the rapid development of computer hardware and software, a few emerging imaging techniques have been gradually applied for on/in-line inspection. However, for other emerging imaging techniques, the major barrier for achieving industrial application is budget constraint because the cost of an image-processing system is still very high. To satisfy the need for cost-effectiveness, developing a cheap specific imaging system is especially critical in the future. Third, exploiting novel and powerful algorithms for data mining and processing is another development trend. For example, hyperspectral imaging can provide abundant spatial information, but the spatial information has not been deeply utilized. Therefore, developing algorithms for extracting spatial information is important. On the other hand, abundant data would take much time during image processing. To accelerate processing speed and meet modern manufacturing requirements, adequate, efficient, and accurate data-processing algorithms are highly required.

6 Conclusions

This review summarized advanced applications of emerging imaging techniques for meat quality and safety detection and evaluation, which included optical imaging, ultrasound imaging, tomographic imaging, thermal imaging and odor imaging. From these applications, it was found that these emerging imaging techniques had the capability to assess external/internal attributes in various types of meat, including pork, beef, lamb, chicken, and fish. In addition, merits and technical limitations of each imaging technique were also presented. Finally, it was concluded that integration of multiple imaging techniques, cost reduction, and developing efficient image-processing algorithms were the 3 main future trends for these emerging imaging techniques.

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Table 1. Advanced applications of emerging imaging technologies for meat quality and safety detection and evaluation since 2000.

Mode	Product	Application	Reference
Ultrasound imaging	Pork	Carcass composition	Ayuso et al. (2013); Youssao et al. (2002); Newcom et al. (2002)
		Quality classification	Fortin et al. (2003)
	Beef	Prediction of marbling grades	Harron and Dony, (2009); Hassen et al. (2001); Fukuda et al. (2013)
		Carcass composition	Ribeiro et al. (2008)
	Chicken	Foreign object detection	Cho and Irudayaraj (2003); Pallav et al. (2009)
X-ray imaging	Pork	Salt concentration	Håseth et al. (2008); Vestergaard et al. (2004)
		Lean meat content Fat and rind	Font i Furnols et al. (2009); Romvári et al. (2006); Vester-Christensen et al. (2009); Picouet et al. (2010) Jensen et al. (2011)
	Beef	Fat and muscle content	Prieto et al. (2010)
	Lamb	Carcass composition	Karamichou et al. (2006); Macfarlane et

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			al. (2006); Navajas et al. (2007)
		Muscularity and eating quality	Navajas et al. (2008)
	Chicken	Bone fragment	Tao et al. (2001); Tao and Ibarra (2000)
		Bone mineral density	Korver et al. (2004)
	Fish	Detecting fish bones	Mery et al. (2011)
		Salt and fat distribution	Segtnan et al. (2009)
Magnetic resonance imaging	Pork	Intramuscular fat content	Davenel et al. (2012); Monziols et al. (2006)
		The lean meat percentage	Collewet et al. (2005)
		Prediction of sensorial characteristics	Cernadas et al. (2005)
		Prediction of body composition	Kremer et al. (2013); Mohrmann et al. (2006)
		Salt content	Hansen et al. (2008); Veliyulin et al. (2009); Vestergaard et al. (2005)
		Water activity	Aaslyng et al. (2003); Ruiz-Cabrera et al. (2004); Vestergaard et al. (2005)
	Beef	Fat content	Ballerini et al. (2002)

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		Water activity	Bouhrara et al. (2011); Bouhrara et al. (2012a; 2012b)
		Muscle structure	Bonny et al. (2001a; 2001b); Laurent et al. (2000)
	Chicken	Moisture and structure changes	Shaarani et al. (2006)
	Fish	Fat content	Brix et al. (2009); Toussaint et al. (2005)
		Water and salt distribution	Aursand et al. (2010); Aursand et al. (2008); Erikson et al. (2004)
		Optimization of salting processes	Guðjónsdóttir et al. (2009); Veliyulin and Aursand (2007)
Fluorescence imaging	Pork	Measurement of lipid oxidation	Veberg et al. (2006)
		Contamination detection	Kim et al. (2003)
	Beef	Contamination detection	Burfoot et al. (2011)
		Measurement of meat composition	Skjervold et al. (2003)
	Lamb	Contamination detection	Burfoot et al. (2011)

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	Chicken	Study the fat distribution	Adedeji et al. (2011)
		Contamination detection	Cho et al. (2009)
		Measurement of lipid oxidation	Wold and Kvaal (2000)
Hyperspectral imaging	Pork	Tenderness	Tao et al. (2012a); ElMasry et al. (2012b); Barbin et al. (2013c)
		Water-holding capacity	Barbin et al. (2012a)
		Chemical compositions	Barbin et al. (2013a)； Qiao et al. (2007a, b);
		Color and pH	Barbin et al. (2012a); Qiao et al. (2007a); Qiao et al. (2005)
		Microbial spoilage	Tao et al. (2010); Peng et al. (2010); Wang and Zhang (2010a, b); Wang et al. (2011); Tao et al. (2012a); Barbin et al., (2013d)
		Quality classification	Tao et al., (2012b); Barbin et al. (2013b)
	Beef	Tenderness	Cluff et al. (2008); Naganathan et al. (2008a, 2008b); Wu et al. (2010); Wu et

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			al. (2012c); Li et al. (2011); ElMasry et al. (2012b)
		Chemical compositions	Kobayashi et al. (2010); ElMasry et al. (2013)
		Color and pH	Wu et al. (2010); Wu et al. (2012c); ElMasry et al. (2012b)
		Microbial spoilage	Peng et al. (2009); Peng et al. (2011)
	Lamb	Tenderness	Kamruzzaman et al. (2013)
		Chemical compositions	Kamruzzaman et al. (2012a)
		Color and pH	Kamruzzaman et al. (2012b)
	Chicken	Wholesome/unwholesome Moisture Contaminant detection Bone fragment Skin tumor detection Springiness	Chao et al. (2007; 2008; 2010); Yang et al. (2010) Kandpal et al. (2013) Park et al. (2002); Windham et al. (2003; 2005); Lawrence et al. (2006) Yoon et al. (2006; 2008) Kim (2004); Du et al. (2007); Fletcher et al. (2003); Kong et al. (2004); Park et al. (2006); Nakariyakul et al. (2009)

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			Xiong et al. (2014c)
		Microbial spoilage	Feng and Sun (2013a; 2013b)
	Fish	Classification	Costa et al. (2011); Sone et al. (2012)
		Texture	Costa et al. (2011); Dai et al. (2014); He et al. (2014); Wu et al. (2014)
		Color and pH Ice fraction Astaxanthin Expired	He et al. (2012); Wu et al. (2012b) Stevik et al. (2010) Dissing et al. (2011) Ivorra et al. (2013)
		Moisture, water-holding capability	Wu et al. (2012a); Wu and Sun (2013a)
		Microbial spoilage	Sivertsen et al. (2011; 2012); Wu and Sun (2013b)
		Frozen-thawed	Zhu et al. (2013)
Thermal imaging	Pork	Detecting meat quality	Costa et al. (2010); Lawrence et al. (2010); Weschenfelder et al. (2013)
		Identification of stress condition	Cordeiro et al. (2012)
	Beef	Prediction of infection	Schaefer et al. (2012); Schaefer et al.

			(2004)
		Measurement of stress and pain	Stewart (2008)
		Prediction of temperature variability	Berry (2000)
	Lamb	Evaluation of climatic conditions	do Prado Paim et al. (2013)
	Chicken	Monitoring of doneness	Ibarra et al. (2000)
		Measuring skin temperature	Marelli et al. (2012)

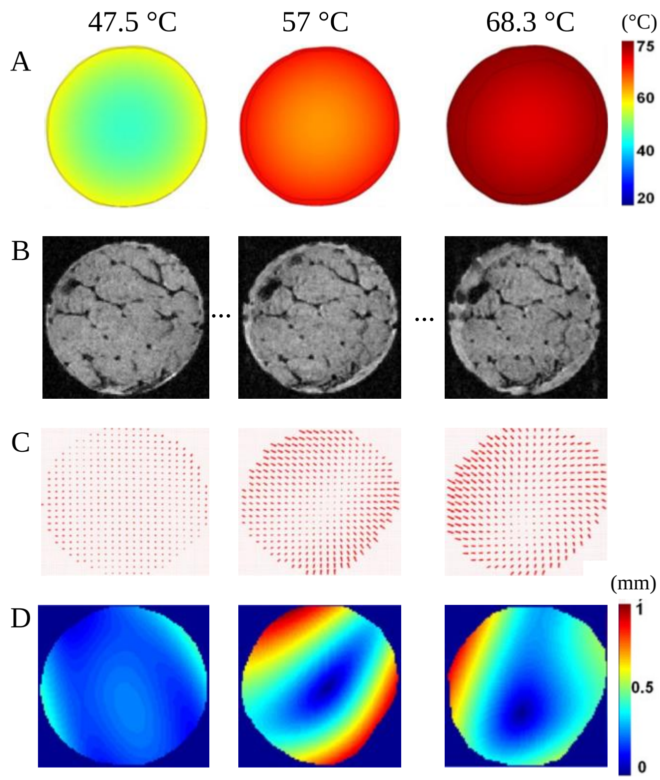

Figure 1. For three average temperatures in the sample: (A) temperature maps obtained by numerical simulation; (B) the corresponding magnetic resonance images; (C-D) representations, in direction and magnitude, of deformation field (Bouhrara et al., 2012).

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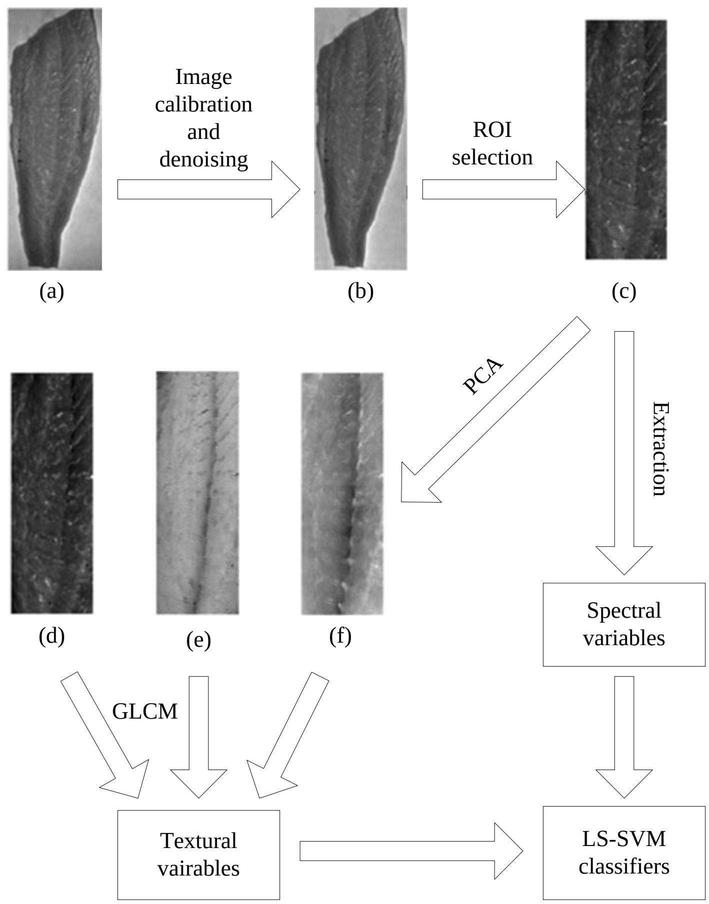

Figure 2. Main steps for integrating spectral information and image information. (a) Raw image, (b) calibrated and denoised image, (c) ROI image, (d-f) PC images 1 through 3 (Zhu et al., 2013).