Meat Science 116 (2016) 110–117

Contents lists available at ScienceDirect

Meat Science

journal homepage: www.elsevier.com/locate/meatsci

Online monitoring of red meat color using hyperspectral imaging

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ARTICLE INFO

Article history:
Received 15 May 2015
Received in revised form 8 December 2015
Accepted 1 February 2016
Available online 3 February 2016

Keywords:
Hyperspectral imaging
Beef
Lamb
Pork
Multivariate analysis
Image processing
Successive projections algorithm

ABSTRACT

A hyperspectral imaging system in the spectral range of 400–1000 nm was tested to develop an online monitoring system for red meat (beef, lamb, and pork) color in the meat industry. Instead of selecting different sets of important wavelengths for beef, lamb, and pork, a set of feature wavelengths were selected using the successive projection algorithm for red meat colors (L*, a*, b) for convenient industrial application. Only six wavelengths (450, 460, 600, 620, 820, and 980 nm) were further chosen as predictive feature wavelengths for predicting L*, a*, and b* in red meat. Multiple linear regression models were then developed and predicted L*, a*, and b* with coefficients of determination ($R^2{}_p$) of 0.97, 0.84, and 0.82, and root mean square error of prediction of 1.72, 1.73, and 1.35, respectively. Finally, distribution maps of meat surface color were generated. The results indicated that hyperspectral imaging has the potential to be used for rapid assessment of meat color.

1. Introduction

Color is an important factor that is commonly used as a quality index to the meat industry and meat science research. Color has been reported to be one of the most important meat quality attributes and significantly influences purchasing decisions (Khliji, van de Ven, Lamb, Manza, & Hopkins, 2010; Ngapo, Martin, & Dransfield, 2007), because consumers use discoloration as an indication of lack of freshness and wholesomeness (Mancini & Hunt, 2005; Phung et al., 2013). Color is also important from the economic point of view as the industry loses money due to undesirable color (Hughes, Oiseth, Purslow, & Warner, 2014). Previous studies have shown that consumers will consider meat acceptable when it falls within a certain threshold value. For instance, consumers of lamb will consider the color acceptable when L* value is equal to or exceeds 34 (Hopkins, 1996; Khliji et al., 2010) and a* value is below 19 (Hopkins, 1996) or equal to or exceeds 9.5 (Khliji et al., 2010). Color has also been shown to be indicative of tenderness because trained panelists have found darker pork steaks to be more tender and juicy than lighter-colored steaks (Norman, Berg, Heymann, & Lorenzen, 2003). Lightness information (L* value) also allows the detection of certain defects in meat such as DFD (dark, firm and dry) and PSE (pale, soft exudative) (Warriss, Brown, & Paściak, 2006). Both DFD and PSE are unattractive to consumers. Therefore, rapid and accurate monitoring of color is essential for the meat industry.

Generally, instruments such as Minolta and Hunter Lab colorimeters are most widely and extensively used for CIE L*a*b* color measurement (Tapp, Yancey, & Apple, 2011). In this color space, L* measures the lightness (varies from 100 for white to 0 for black); a* denotes the red–green or redness; and b* indicates the yellow–blue or yellowness. The range of both a* and b* is between −128 and 128 (CIE, 1978). Although color measurements using these conventional instruments are rapid and simple, they are used to measure color by scanning a number of small random spots on the meat surface as the average of the sample. Thus, their measurements cannot be representative for the whole surface. Therefore, this type of approach has a limitation in terms of repeatability and accuracy (Larraín, Schaefer, & Reed, 2008; Tapp et al., 2011), as the meat surface is heterogeneous and discoloration occurs on random areas including the edge of the meat, which is very difficult to scan with colorimeters (Trinderup & Kim, 2015). Moreover, these conventional instrumental methods are not suitable for online monitoring in fast-paced production and processing environments where the whole surface of the sample must be inspected. Another potential disadvantage of conventional instrumental measurements is the lack of spatial information. Indeed, for detailed understanding and characterization of a meat sample and thereby more precise quality evaluation, it is essential to know the color intensity of each pixel on the sample surface (Leon, Mery, Pedreschi, & Leon, 2006). Thus, automatic pixel-based color measurement processes are necessary for online monitoring of red meat color in the industry.

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http://dx.doi.org/10.1016/j.meatsci.2016.02.004
0309-1740/

As an emerging technology, hyperspectral imaging can be effectively used for online monitoring if properly optimized. Because of its outstanding characteristic identification capabilities and rich physical and chemical information, hyperspectral imaging has proved its potential as a popular method for performing rapid, nondestructive analyses on a wide variety of matrices across agriculture produce including fruits and vegetables (Menesatti et al., 2009; Taghizadeh, Gowen, & O'Donnell, 2009), meat (Barbin, ElMasry, Sun, & Allen, 2012a; ElMasry, Sun & Allen, 2012b; Kamruzzaman, ElMasry, Sun, & Allen, 2011; Kamruzzaman, Sun, ElMasry, & Allen, 2013a; Kamruzzaman, Makino, & Oshita, 2016; Pu, Sun, Ma, Liu, & Kamruzzaman, 2014; Pu, Xie, Sun, Kamruzzaman, & Ma, 2015; Wold, O'Farrell, Høy, & Tschudi, 2011), poultry (Feng & Sun, 2013), ham (Gou et al., 2013; Iqbal, Sun, & Allen, 2013) and seafood (Wu, Sun, & He, 2012). Despite the immense advantages, hyperspectral imaging technology cannot be directly implemented in online monitoring because of the extensive time required for processing the huge volume of data. However, the technique can be used as a precursor to a dedicated multispectral online system (Pu, Kamruzzaman, & Sun, 2015). To build a multispectral vision system, optimal spectral bands should be identified from hyperspectral data analysis (ElMasry, Kamruzzaman, Sun & Allen, 2012a; Kamruzzaman, Makino, & Oshita, 2015a; Kamruzzaman, Nakauchi, & ElMasry, 2015b). Once these bands are identified, a simple and cost-effective multispectral system can be engineered for industrial applications.

To date, research on red meat quality using hyperspectral imaging has focused separately on beef (ElMasry et al., 2012b), pork (Barbin et al., 2012a), and lamb (Kamruzzaman et al., 2012a). Consequently, different combinations of feature wavelengths were selected for the same constituent in different types of red meat. For example, the near infrared (NIR) hyperspectral imaging system has been used for selecting optimum wavelengths for predicting L^* value in beef (ElMasry et al., 2012b), lamb (Kamruzzaman et al., 2012a), and pork (Barbin et al., 2012a). Weighted regression coefficients resulting from partial least squares regression (PLSR) (Wold, Martens, & Wold, 1983) models were used to identify optimum wavelengths correlated with L^* values. Although the same equipment, methods, and parameters were tested, different combinations of feature wavelengths were selected for different types of meat: for pork L^*: 947, 1024, 1124, 1208, 1268, and 1654 nm; for beef L^*: 947, 1078, 1151, 1215, 1376, and 1645 nm; and for lamb L^*: 940, 980, 1037, 1104, 1151, 1258, 1365, and 1418 nm. Thus, for developing a multispectral system, different combinations of wavelengths should be used to determine the same attribute in different red meats; however, it results in inconvenience to processors. The same scenario has been reported for other attributes such as chemical composition and tenderness of beef (ElMasry et al., 2012b; ElMasry, Sun, & Allen, 2012c), lamb (Kamruzzaman, ElMasry, Sun, & Allen, 2012c; Kamruzzaman, ElMasry, Sun, & Allen, 2013b), and pork (Barbin, ElMasry, Sun, & Allen, 2012b; Barbin, Valous, & Sun, 2013). No research has been conducted thus far for selecting feature wavelengths to design real-time spectral imaging instruments for the meat industry instead of selecting different sets of important feature wavelengths for each red meat. Accordingly, we decided to conduct a comprehensive study combining beef, lamb, and pork to identify effective feature wavelengths suitable for use in a multispectral imaging system for convenient industrial application. Thus, the main objective of this study was to evaluate the feasibility of using hyperspectral imaging in the spectral range 400–1000 nm to select effective feature wavelengths suitable for use in a multispectral online system for monitoring color parameters of red meat for the meat industry. The specific objectives were to (a) establish quantitative relationships between spectral data and reference color values (L^*, a^*, and b^*) using PLSR and least-squares support vector machine (LS-SVM), (b) compare the prediction ability of PLSR and LS-SVM, (c) select feature wavelengths suitable for use in a multispectral imaging system for online monitoring of red meat color, (d) develop quantitative functions using multiple linear regression (MLR) for online predictions, and (e) develop pixel-wise image processing algorithms to generate distribution maps of color values.

2. Materials and methods

2.1. Sample preparation and reference color measurements

Fresh beef, lamb, and pork samples (29 each) were collected from the loin muscle (*m. longissimus thoracis et lumborum*) at 2 day postmortem from a local slaughterhouse in Tokyo, Japan. Each muscle (2-cm thick) was individually labeled and vacuum packed and then transported to the laboratories of Bioprocess Engineering at the University of Tokyo, Japan. Samples were bloomed for 30 min before image acquisition and color measurements. Each muscle was first scanned with the hyperspectral imaging system described below, and its reference value of color was then determined with a Minolta CR-400 colorimeter (Konica Minolta Corp., Japan) with a closed cone, using a standard D65 illuminant with a light source of pulsed xenon lamp and a standard observer of 2^o and an aperture size of 8 mm. The colorimeter was calibrated with a standard white calibration plate before color measurement. The color values were measured in the CIE $L^*a^*b^*$ color space. Color values were obtained as the average of three measurements performed on different locations of each sample. Color was measured on the same surface of the muscles where the hyperspectral images were acquired. A total of 45 frozen samples (approximately 1/3 of total samples, 15 from each species) originating in different geographical regions (Australia, Canada, Mexico, New Zealand, and USA) were also collected to ensure that the model would apply both locally and globally. Frozen samples were thawed overnight at 4 °C. Each sample was then removed from the vacuum package, left for 30 min for blooming and surface moisture was wiped by paper towels before image acquisition and color measurements. For industrial application, an automatic system can be easily designed over the conveyor belt with the minimum modifications of the production line to wipe the surface of meat steaks. In total, 132 samples including 44 each of beef, lamb, and pork were used for the investigation. To ensure the credibility and reliability of wavelength selection to design a multispectral online imaging system, samples were collected from four different slaughter batches as well as from different quality grades to ensure wide variations in color values that may be found during routine sampling. The complete procedures for selecting feature wavelengths for the design of online multispectral systems are depicted in Fig. 1.

2.2. Hyperspectral imaging system

The hyperspectral images of samples were captured by a visible near-infrared (VNIR) hyperspectral imaging system (400–1000 nm) in reflectance mode in a dark room to avoid stray light from the surroundings at a controlled temperature (20 °C) and humidity (65%). The main components of this instrument, as shown schematically in Fig. 2 are a 12-bit charge-coupled device (CCD) camera, a line-scanning spectrograph coupled with a C-mount lens with fixed distance of 330 mm from sample surface, an illumination unit with one 50-W tungsten halogen and one xenon lamp adjusted at a 45° angle to illuminate the camera's field of view, a translation stage driven by a stepping motor with a user-defined speed, and a computer with data acquisition software. A more detailed description of the hyperspectral imaging system used in this study may be found elsewhere (Kamruzzaman, Makino, Oshita & Liu, 2015c; Kamruzzaman, Makino & Oshita, 2015d).

2.3. Image acquisition and correction

Each sample was placed on a black background with very low reflectance to obtain good contrast between the sample and background and conveyed to the field of view of the camera to be scanned line by line to create a three-dimensional hypercube. The speed was set at 1.08 mm/s