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Hyperspectral imaging for real-time monitoring of water holding capacity in red meat

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ABSTRACT

A hyperspectral imaging system was investigated for determination of feature wavelengths to be used in a design of a multispectral system for real-time monitoring of water holding capacity (WHC) in red meat. Hyperspectral images of different red meat samples were acquired in the spectral range of 400–1000 nm and partial least-squares regression (PLSR) and least square support vector machine (LS-SVM) models were developed. Feature wavelengths were selected using regression coefficients (RCs) and competitive adaptive reweighted sampling (CARS). The best set of feature wavelengths was determined using RCs and the best calibration model obtained was based on RCs-LS-SVM. The model obtained an R^2p of 0.93 and RPD of 4.09, indicating that the model is adequate for analytical purposes. An image processing algorithm was developed to transfer this model to each pixel in the image. The results showed that instead of selecting different sets of wavelengths for beef, lamb, and pork, a subset of feature wavelengths can be used for convenient industrial application for the determination of WHC in red meat. The pixel wise visualization of WHC obtained with the aid of image processing was another advantage of using hyperspectral imaging that cannot be obtained with either imaging or conventional spectroscopy.

1. Introduction

Water holding capacity (WHC), defined as the ability of fresh meat to retain its water during processing, storage, and cooking, is one of the most important technological quality attributes of red meat that can affect consumer preferences. The WHC has a great influence on the appearance of fresh meat in retail and might affect the sensory properties of cooked meat (Pedersen, Morel, Andersen, & Engelsen, 2003). Poor WHC owing to high drip loss is an undesirable quality of meat, and thus reduces consumer acceptability. If WHC is properly managed, many other operational variables will consequently improve, which will result in greater consumer satisfaction with products. From an economic outlook, high WHC (less drip loss) is extremely desirable because meat is sold by weight (Hoving-Bolink et al., 2005). Therefore, controlling WHC is very important for the meat industry to maximize yield and quality. Practically, WHC can be determined by three fundamentally different principles such as drip loss, filter paper test, and cooking loss (Prevolnik, Čandek-Potokar, & Škorjanc, 2010). These techniques are time consuming and involve destructive sampling and therefore, are not optimally suitable for on-line industrial applications.

Recently, hyperspectral imaging has emerged as one of the most efficient and advanced tools for non-destructive evaluation for a variety of applications (Kamruzzaman, Makino, & Oshita, 2015b). Hyperspectral imaging is a combination of both imaging and spectroscopy in a single instrument to acquire both spatial and spectral information simultaneously from an object. Although it was originally developed for remote sensing applications, hyperspectral imaging has now found its way into many diverse applications (ElMasry, Kamruzzaman, Sun & Allen, 2012). Considerable research has proved the potential of hyperspectral imaging in meat quality assessment (Barbin, ElMasry, Sun, & Allen, 2012a; ElMasry, Sun & Allen, 2011; Iqbal, Sun, & Allen, 2013; Kamruzzaman, ElMasry, Sun, & Allen, 2011; Park et al., 2011). However, the

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technology is not yet suitable for routine online monitoring due to the challenges in analyzing a vast amount of hyperspectral image data. The time spent in the image acquisition and analysis is high. On the other side, spectra contain not only useful information but also redundant and irrelevant information (i.e., noise) and collinearity between wavelength variables. Indeed, the redundant and irrelevant information in the spectra complicates the model, leading to inaccurate prediction. Removing uninformative variables and extracting informative variables not only reduces the computational load but also produces stronger and more stable prediction models (Burger & Gowen, 2011). Therefore, it is very important to select appropriate wavelengths from hyperspectral data analyzes for designing multispectral real-time monitoring systems. If the spectral bands are properly selected to facilitate the design of multispectral imaging systems, which usually operate on ten wavelengths or less, the technology would certainly be an improvement on existing technology for process monitoring and real-time inspection (Qin, Chao, Kim, Lu, & Burks, 2013). The acquisition time, complexity, and cost of these systems will generally be quite low compared to hyperspectral imaging (Park et al., 2011; Pu, Kamruzzaman, & Sun, 2015). Hence, multispectral imaging with selected feature wavelengths is an alternative and promising approach for online screening in the industry.

Recently, various studies have investigated hyperspectral imaging for selecting effective wavelengths aimed at encouraging the manufacture of online multispectral imaging instruments for beef (ElMasry et al., 2011), lamb (Kamruzzaman, Barbin, ElMasry, Sun, & Allen, 2012; Kamruzzaman, ElMasry, Sun & Allen, 2013; Kamruzzaman, Sun, ElMasry & Allen, 2013), and pork (Barbin et al., 2012a; Tao, Peng, Li, Chao, & Dhakal, 2012). In particular, one research group investigated near infrared (NIR) hyperspectral imaging (900–1700 nm) and proposed feature wavelengths for designing a multispectral imaging system for online monitoring of various quality attributes of beef (ElMasry, Sun & Allen, 2012; ElMasry et al., 2011), pork (Barbin, ElMasry, Sun & Allen, 2012b; Barbin et al., 2012a), and lamb (Kamruzzaman, ElMasry, Sun, & Allen, 2012a, 2012b). Although all these studies were performed using a common system with an identical reference and data analysis method, surprisingly different combinations of optimum wavelengths were selected for the same constituent in different types of red meat. This implies that to develop a multispectral system, different combinations of wavelengths need to be used to determine the same attribute in different types of red meat, which is not convenient and feasible for the processors. Therefore, for convenient industrial application, comprehensive research should be conducted combining all types of red meat to select a subset of feature wavelengths for multispectral prediction for a particular application.

Currently, both VIS/NIR (400–1000 nm) and NIR (900–1700 nm) hyperspectral imaging systems are widely used for meat quality assessment due to their respective benefits and drawbacks. However, the VIS/NIR range is industrially advantageous because of the wide availability and low cost of charge-coupled device (CCD) detectors compared to the indium gallium arsenide (InGaAs) detectors used in the NIR region (Qin et al., 2013). Therefore, the key aim of this study was to use a VIS/NIR hyperspectral imaging system (400–1000 nm) for selecting some important feature wavelengths to develop a real-time multispectral imaging system for monitoring of WHC in red meat for the meat industry. The specific objectives were to (a) establish quantitative relationships between spectral data and reference WHC values using PLSR and LS-SVM, (b) select some feature wavelengths to design a multispectral imaging system for real-time monitoring of WHC in red meat (c), and (d) develop image processing algorithms to generate distribution maps of WHC.

2. Material and methods

2.1. Sample collection and measurements of reference WHC

Fresh beef, lamb, and pork samples from *M. longissimus dorsi* (LD) were collected from a local slaughter house in Tokyo, Japan. Each muscle (2 cm thickness) was individually labeled and transported to laboratories of Bioprocess Engineering, The University of Tokyo, Japan. Each muscle was first scanned by the hyperspectral imaging system as described by Kamruzzaman et al. (2015a), Kamruzzaman Makino, Oshita (2016) and the reference WHC value for each muscle was then determined by using the drip loss method (Honikel, 1998). It is necessary to include a large number of samples representing a wide variation in WHC for the development of a calibration model (Berzaghi & Riovanto, 2009). In this study, it was done by including samples from different geographical origin, different quality grades, and different slaughter batches. Thereafter, some frozen samples from different geographical origin were collected (Australia, Canada, Mexico, New Zealand, and USA) to obtain a wide variation in WHC measurements to ensure that the model is representative both locally and globally as well as to ensure the credibility and reliability of wavelength selection to design a multispectral online imaging system. The frozen samples were thawed overnight at 4 °C before image acquisition. Within the drip loss method, the loss of water was determined as a percentage of weight loss from a 2.5 cm × 2.5 cm × 2.0 cm (length × width × thickness) cut slice suspended in a plastic jar for 48 h storage at 4 °C. Measurements were conducted in duplicate in each muscle and averaged to express drip loss for each muscle. In total, 120 samples, incorporating 40 samples from each red meat type were used for the investigation. These samples were systematically divided into a calibration and prediction set. To ensure that both groups appropriately covered a similar range of reference values, samples were first sorted in descending order with respect to the reference WHC for each red meat type, following which every third sample was selected to compose a prediction set. In this way, 39 samples incorporating 13 samples from each red meat type were selected as a prediction set, whereas the remaining 81 samples including beef (27), lamb (27), and pork (27) were used as a calibration set. The statistics such as mean, standard deviation (SD) and range of these samples are shown in Table 1. The complete procedures for selecting feature wavelengths for the design of online multispectral systems are depicted in Fig. 1.

2.2. Image acquisition and image correction

The image acquisition was conducted in a dark room to avoid any undesired stray light, and at a controlled temperature and humidity of 20 °C and 65%, respectively. Hyperspectral images were acquired in the spectral range of 400–1000 nm with 5 nm intervals between contiguous bands with 121 spectral bands. The acquired raw images were corrected with two reference images using the following equation:

$$R = \frac{R_0 - D}{W - D} \tag{1}$$

where R is the relative reflectance image of the sample, R_0 is the raw image of the sample, W is the white reference image acquired from a uniform, stable, and high reflectance, ceramic tile (~99% reflectance), and D is the dark current image acquired by completely covering the camera lens with its non-reflective opaque black cap.