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APPLICATION OF HYPERSPECTRAL IMAGING TECHNIQUE FOR DETERMINATION OF PORK QUALITY ATTRIBUTES

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ABSTRACT Meat grading has always been a research subject because of its economical importance and the large variations among meat product qualities. In this study, a hyperspectral imaging system in the near-infrared (NIR) range (900-1700 nm) was developed for quality assessment of pork meat. Pork samples were classified in three quality grades, as reddish-pink, firm and non-exudative (RFN), pale, soft and exudative (PSE), and dark, firm and dry (DFD) based on colour, texture and exudation of the meat. Spectral information obtained has shown that there are differences among pork meat quality classes that allows for classification of samples based on spectral features. Some significant wavelengths linked to drip loss, pH and colour attributes were identified by using first derivative of the spectra. Principal component analysis (PCA) has shown that spectral information can distinguish pork meat according to quality characteristics. Results are encouraging and show the promising potential of hyperspectral technique applications for fast and non-destructive assessment of pork quality.

Keywords: pork, meat quality, hyperspectral imaging, principal components.

INTRODUCTION Sensory appearance and textural patterns of fresh meat products are directly linked to some chemical properties such as water holding capacity, marbling and protein contents, representing important criteria for meat quality characterization. Pork quality is the result of a complex combination of factors, with interactions among the sensory environment, genotype and nutritional environment combining with peri-mortem metabolism to influence final meat quality (Purslow et al., 2008). Conventional meat grading routines and quality evaluation methods are laborious, time-consuming and destructive in addition to be linked to inconsistency and variability due to human inspection. The pork producers need efficient technologies for assessment of pork quality in order to save time and cost.

Hyperspectral imaging refers to the imaging of a scene over a large number of contiguous spectral bands such that a complete reflectance spectrum can be obtained for the region being imaged. In recent years there have been growing interests in this technology from researchers around the world regarding its application for food products. Application of hyperspectral imaging for direct pork meat quality determination such as drip loss, pH, marbling, texture and exudation has recently been investigated (Qiao et al., 2007a, b, c) using a pushbroom hyperspectral imaging system in the visible and very near infrared range (400-1000nm). The research works described provided good references and resources for dealing with various problems associated with non-destructive methods for fast detection of food quality. However, to our knowledge no research has been conducted using hyperspectral imaging in the near-infrared range for pork samples. On the contrary, there are some research endeavours for studying the applicability of hyperspectral imaging for quality evaluation of beef, chicken and fishes (Peng and Wu, 2008; Yang et al., 2009; ElMasry and Wold, 2008). There is a need for studying the unique features of this technology and obtaining the fundamental information that will be useful for designing the future real-time quality detection system.

The overall objective of this research is to investigate the potential of using hyperspectral reflectance imaging in the near-infrared region (900-1700) for pork quality detection. Specific objectives were to:

Developing a hyperspectral imaging system in the NIR region,

Applying Principal Component Analysis (PCA) to differentiate pork meat from several quality attributes, and

Identify several important wavelengths that can be utilized by a future multispectral imaging system.

MATERIALS AND METHODS

Sample preparation

A set of 75 fresh pork chops (one inch in thickness) from the *longissumus dorsi* muscle was prepared at Teagasc Food Research Centre Ashtown (Dublin, Ireland) and then vacuum packed and sent to the Computerized Food Technology Laboratory at UCD Belfield, Dublin, Ireland for image acquisition and subsequent analyses.

Measurement of quality attributes

Meat quality attributes were measured at 2 days post-mortem. Drip loss was determined as a percentage of weight loss after 1 day storage at 4ºC (Honikel, 1998). After one hour blooming period, colour and pH were measured. Four pH measurements were acquired for calculating the average for ultimate pH of the loin eye using a pH meter (Orion 3 Star, Thermo Fisher Scientific Inc., USA). For colour assessment, six measures were performed for obtaining the average colour parameters (L, a* and b*) on the loin eye of each chop with a Minolta colorimeter (CR-400, Konica Minolta Corp., Japan).

The samples were classified in three different quality grades based on lightness value of colour (L), ultimate pH and drip loss according to Warner et al. (1997) resulting in 40 samples classified as RFN, 20 samples as PSE and 15 samples as DFD. After performing this classification, each sample was scanned for hyperspectral image acquisition.

Hyperspectral image collection and processing

Hyperspectral imaging system

Figure 1 shows a picture of the hyperspectral imaging system used and its main components. The system is of a pushbroom mode consisting of spectrograph (ImSpector, N17E, Spectral Imaging Ltd, Finland), a camera (Xeva 992, Xenics Infrared Solutions, Belgium), illumination source (tungsten-hallogen V-light, Lowel Light Inc, USA), a conveyer (MSA15R-N, AMT-Linearways, SuperSlides & Bushes Corp., India) and a computer supported with a data acquisition software (SpectralCube, Spectral Imaging Ltd., Finland),. The spectrograph had a fixed-size internal slit (30 µm) to define a field of view (FOV) for the spatial line (horizontal pixel direction) and collected spectral images in a wavelength range of 900-1750 nm with a total of 256 bands. The conveyer was driven by a stepping motor (GPL-DZTSA-1000-X, Zolix Instrument Co, China) with a user-defined speed of 2.7cm/s.

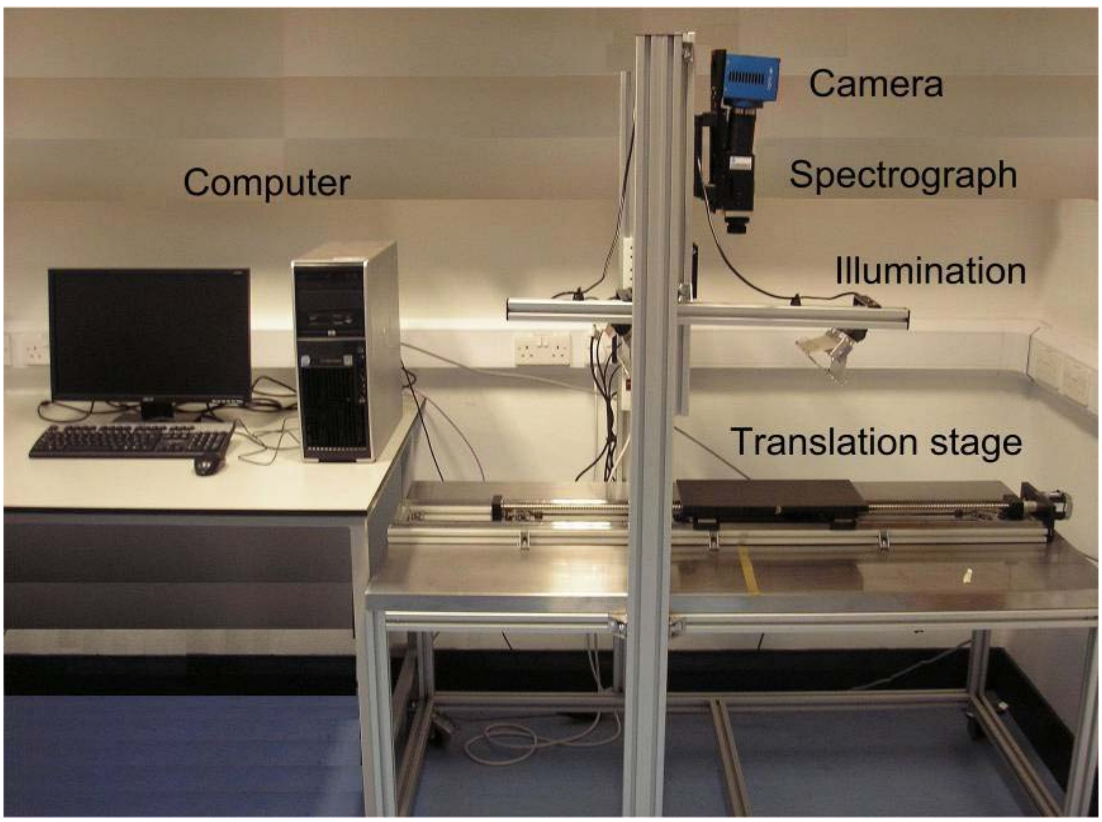

Figure 1. Hyperspectral imaging system used for image acquisition

Image acquisition

During image acquisition, each pork sample was transported by the conveyer to the field of view (FOV) of the camera, where image was taken and stored in the computer. The image acquisition process was controlled by the SpectralCube software. The images were then stored in a raw format before processed. One hyperspectral image was acquired for each sample.

Image pre-processing

A visual inspection of the acquired images and their corresponding spectra revealed that the spectral images from the first four and the last fifteen bands had a high level of noise, thus being not useful for data extraction. The images were then resized to 237 bands for spectral information, ranging from 910 to 1700 nm.

To correct the images from the dark current of camera, dark and white hyperspectral images were also acquired. Both images were used to calibrate of the original hyperspectral images. A corrected reflectance image was calculated with Equation (1):

$$I = \frac{I_0 - B}{W - B} \quad (1)$$

where I was the relative-reflectance of an image; W was the reference image obtained from a white reference tile and B was the dark current image acquired with the light source off and a cap covering the lens.

A region of interest (ROI) was manually selected comprising only the whole loin eye area. The loin eye spectral information was used for comparison with the physical quality attributes measured. For each image, a mean reflectance spectrum (910 to 1700 nm) of the ROI was calculated by averaging the spectral responses of all pixels in the ROI. In total, 75 mean reflectance spectra were obtained, one for each sample. ROI selection and reflectance spectra extraction from the hyperspectral images were performed using ENVI 4.6.1 (ITT Visual Information Solutions, Boulder, CO, USA).

Data analysis

PCA is a form of factor analysis that seeks a linear combination of variables such that the maximum variance can be extracted from data. It then removes this variance and seeks a second linear combination which explains the maximum proportion of the remaining variance, and this procedure is repeated several times, resulting in orthogonal (uncorrelated) factors. It is commonly used to reduce a large number of variables to a smaller number of factors for data modelling or to select a subset of variables from a larger set. In this study, principal component analyses were performed on the spectral data of pork samples and the resulting loadings were then used to extract the useful information attributed to difference in pork meat qualities according to the values of colour, pH and drip loss. First derivative was performed for the extracted spectral data of the tested quality grades to identify the main wavelengths in the wavelength range studied. The data analysis and image processing procedures were executed using Matlab 7.7.0 (The MathWorks Inc, MA, USA).

RESULTS AND DISCUSSION

The typical average reflectance spectra and the first derivative of the 40 RFN, 20 PSE and 15 DFD samples analyzed in the range from 910-1700nm are shown in Figure 2.

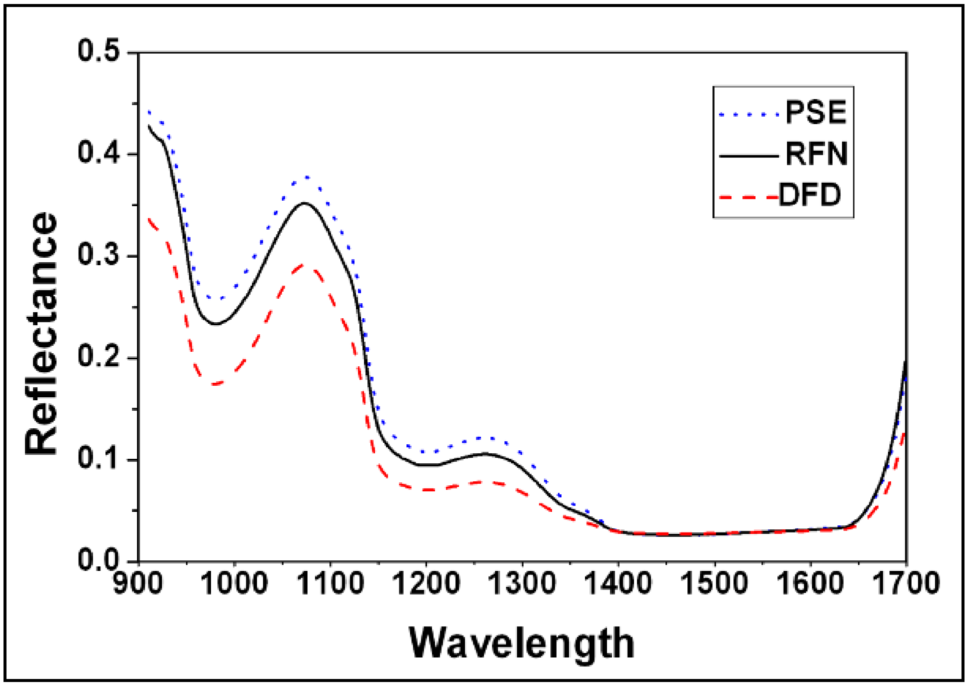

Figure 2. Average mean reflectance spectra obtained for three different pork quality classifications: Pale, soft and exudative (PSE), Reddish-pink, firm, non-exudative (RFN) and dark, firm and dry (DFD) pork.

Each spectrum represents the average for the loin eye area of the tested samples. The different spectra showed similar patterns, but differ on the reflectance absolute values mainly in the range from 910 to 1400 nm. The simple correlation analysis presented in Figure 3 confirmed this observation by showing higher module values for the quality attributes in the same range. Colour and drip loss are directly correlated with the reflectance values, while pH is inversely correlated. DFD samples showed the lowest reflectance values along the spectra, while PSE samples had the highest values. It was also observed a slight difference in the range above 1650 nm.

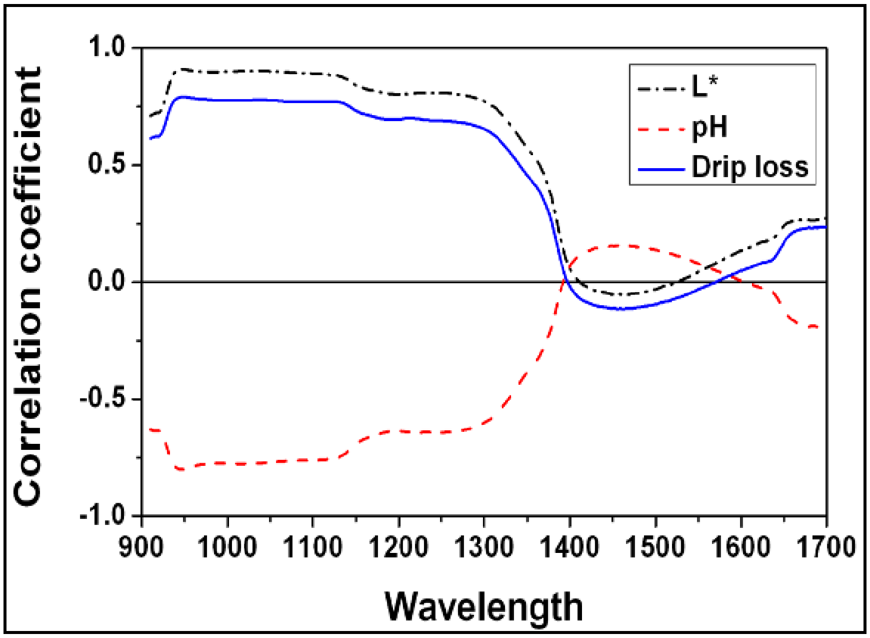

Figure 3. Correlation coefficient for wavelengths vs. colour lightness (L*), pH and drip loss

First derivative average spectra allow for the visualization of greater spectral detail. The derivatives show the location of maximum spectral variance, where more important features are identified, at 947, 1134, 1201, 1318 and 1378 nm, as shown in Figure 4. These wavelengths can be used for further tests to identify and classify pork meat with reduced data processing.

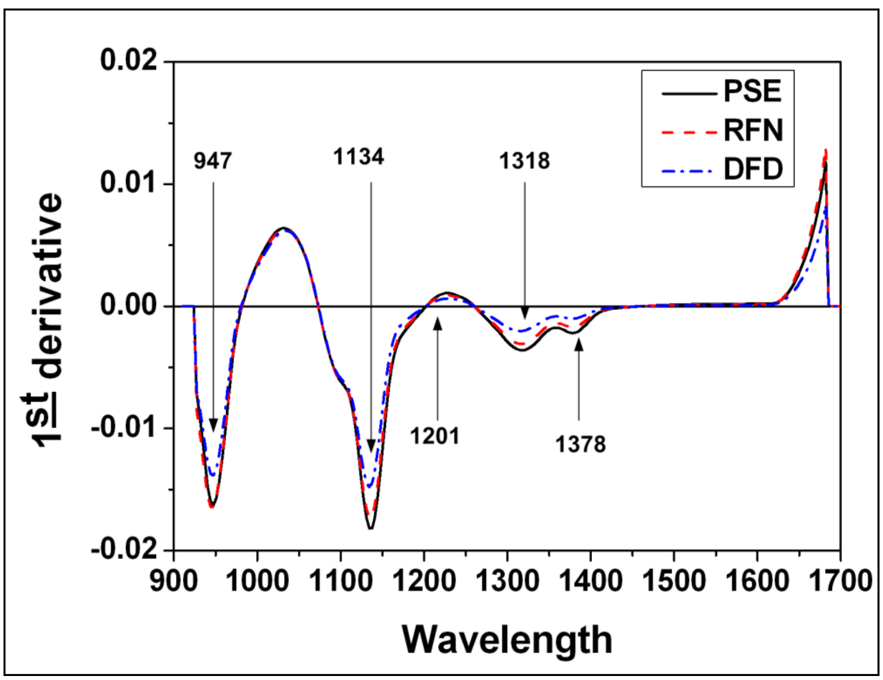

Figure 4: First derivative obtained for three different pork quality classifications: Pale, soft and exudative (PSE), Reddish-pink, firm, non-exudative (RFN) and dark, firm and dry (DFD) pork.

The first three principal components are responsible for 99.4% of variability of the data; the first, second and third principal components variability are 82.3%, 14.3% and 2.8%, respectively.

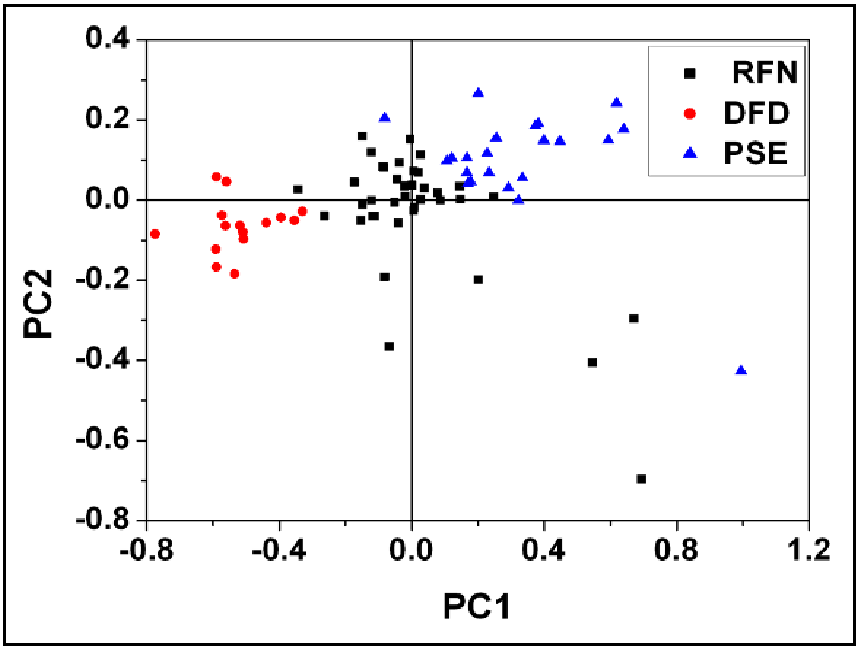

Figure 5. Principal components analysis of the spectral data at the selected wavelengths (947, 1134, 1201, 1318 and 1378 nm).

As shown in figure 5, almost all PSE samples are located in the positive area of both PC1 and PC2, while the DFD samples are almost entirely located in the negative area. The principal components method is able to differentiate pork samples based on the reflectance values obtained.

CONCLUSION The study demonstrated the potential of NIR hyperspectral imaging coupled with principal components analysis for evaluating quality attributes of pork meat. The pork samples from different quality grades could be distinguished through drip loss, pH and colour. A NIR hyperspectral imaging system was used to measure the reflectance spectra from pork samples in the wavelength range between 910 and 1700 nm. PCA was used to extract useful image features allowing for the differentiation of pork meat from different quality classes. Optimal wavelengths were identified using first derivative analysis. Five sensitive wavelength bands were selected that could be potentially utilized by a multispectral imaging system for classifying pork meat in real time. Further work will be performed to develop algorithms for image processing and classification based on the selected optimal wavelengths for pork quality assessment.

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