Determination of Drip Loss in Beef by NIR Hyperspectral Imaging and Multivariate Analysis

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ABSTRACT

Non-destructive determination of drip loss in fresh beef using near infrared (NIR) hyperspectral imaging was evaluated. Different beef muscles were tested and the spectral features from their hyperspectral images were extracted. The spectral data were analyzed by several multivariate analysis approaches such as principal component analysis (PCA) and partial least squares regression (PLSR). The results indicated that drip loss was satisfactorily predicted with high coefficients of determination ($R^2$) of 0.92 and low standard error from cross validation (SECV) of 0.26. Image processing algorithm was then developed to convey the prediction model to each pixel in the image. Recognition the difference in drip loss within the sample and among the muscles emphasized the capability of hyperspectral imaging as a non-invasive technique for meat quality assessment.

Keywords: Hyperspectral imaging; Drip loss; meat, beef; quality; multivariate analysis.

INTRODUCTION

The lack of fast, reliable and non-destructive methods for determining meat characteristics in the carcass and meat cuts has been one of the main obstacles for the development of quality control in the meat industry. In the meat industry, in order to reduce economic losses during processing, as well as to supply high-quality products consistently, quality control procedures must be carried out [1, 2].

The recent applications of hyperspectral imaging systems as an analytical tool in quality assurance of various food products are receiving a growing interest and attention. The simultaneous spatial and spectral information provided by this system along with its non-invasive and chemical-free nature nominated this technology to be a deliberated tool for continuous monitoring of food production processes and for consistent optimization of production systems. Hyperspectral imaging has been emerged by integrating both spectroscopy and imaging techniques in one system to provide detailed information of the tested products which otherwise cannot be achieved with either conventional imaging or spectroscopy alone [3].

The main traits used by consumers to select his preferable fresh meat products depend profoundly on colour, amount of visible fat (marbling) and wetness (exudation). The acceptable meat by consumers should be uniform in colour, little visible fat and a high water holding capacity (less drip loss). Also, eating quality is as important as physical appearance of the meat at the time of purchase. Moreover, meat processors usually use fundamental factors such as pH in combination with water holding capacity to choose raw meat for subsequent processing. Much of the water inside meat muscle is held within the myofibril by capillary forces arising from the arrangement of the thick and thin filaments within the myofibril [4].

The quality of fresh meat depends to a large extent on drip loss which is technologically and economically important not only for food-processing industry but also for consumers as an important attribute during purchasing meat [5]. From economic point of view, low drip loss is extremely desirable because meat is sold by weight and any water loss leads to a reduction in yield due to loss in the total weight of the meat [6, 7]. Moisture is lost after slaughter in the form of drip while the carcass is still in the chilling room and when fresh cuts are in the retail display counter. The drip loss has a great influence on the appearance of fresh meat.
during retail and might affect the sensory properties of cooked meat [8]. In the retail store, moisture loss due to high drip loss results in the drip remaining in the package and appeared as red liquid in the bottom of the package which gives the meat an unattractive appearance, leading to loss of sales [9]. Unfortunately, most traditional techniques to determine fundamental meat quality parameters (including drip loss) are extremely time consuming, expensive and destructive [10] which encouraged introducing novel analytical methods, among which spectral technique such as hyperspectral imaging method is particularly interesting. Given the limited information on the usefulness of hyperspectral imaging systems to predict drip loss in beef, the main aim of this study was to investigate the potential of hyperspectral imaging system in the NIR region of 900-1700 nm for predicting drip loss of beef.

**MATERIALS & METHODS**

**Beef Samples**

Samples of one-inch thick slices were collected from three muscles (*M. longissimus dorsi* (LD), *M. semitendinosus* (ST) and *Psoas Major* (PM)) excised from 27 bulls of three different breeds (Holstein-Friesian, Jersey × Holstein-Friesian and Norwegian Red × Holstein-Friesian). Slices from different breeds and different muscles to a high extent guarantee a large variation in drip loss values, which is critically important to build multivariate prediction models. Each slice was first scanned by the hyperspectral imaging system and then its reference value of drip loss was determined. The loss of water from two 2.5 cm thick cuts from each sample suspended for 48 h in double plastic bags at +4°C was registered [11].

**Configuration and Main Components of the System**

Each slice was then imaged individually in the line-scan pushbroom NIR hyperspectral imaging system of spectral range of 910-1700 nm (with 237 bands). The system consists of a spectrograph (ImSpector N17E, Specim, Spectral Imaging Ltd, Oulu, Finland), a camera (Xeva 992, Xenics Infrared Solutions, Belgium), an illumination unit (Lowel Light Inc., NY, USA), a translation stage operated by stepper motor (GPL-DZTSA-1000-X, Zolix Instrument Co. Ltd, China) and a computer supported with SpectralCube data acquisition software (Spectral Imaging Ltd., Finland). With this pushbroom configuration, beef sample was placed on the translation stage to be scanned line by line using 10 ms exposure time to build a hyperspectral image (R₀) called ‘hypercube’. All image acquisition parameters such as motor speed, exposure time, binning mode and wavelength range were entirely controlled the by SpectralCube data acquisition software.

The raw acquired images were corrected using two extra images acquired for dark (B) and standard white references (W) in order to cancel out the effects of illumination and detector sensitivity and geometry using the expression: $R = 100 \times (R_0 - B) / (W - B)$

**Image Segmentation and Extracting Spectral Data**

To extract spectral information from each beef slice in the hyperspectral image, the image was segmented to isolate the slice into a homogenous background. Because the main interest is to segment only the lean part of the samples in a separate mask, fat pixels was deducted from image. The resulting lean mask (only lean without fat) was then acted as the main region of interest (ROI) from which spectral information of the beef slice was extracted. All processes of image correction, segmentation and spectral data extraction were programmed in Matlab 7.7 (The Mathworks Inc., Natick, MA, USA).

**Multivariate Data Analysis**

The extracted spectral data from all slices were first arranged in a matrix (X) where the rows of this matrix represent the number of samples (slices) and the columns represent the number of variables (237 wavelengths). In addition, one column vector (Y) containing the real measured values of drip loss of the slices was concatenated to this matrix to represent reference drip loss measurements. The calibration model is simply a regression model that will allow the prediction of chemical composition based on spectral data [12]. Therefore, principal component analysis (PCA) was first applied to the spectral data (X) to obtain an overview of systematic spectral variations. Calibrations and predictions of drip loss in beef samples based on spectral information were performed with partial least squares regression (PLSR). Partial least squares regression (PLSR) compresses the spectral data into orthogonal structures called latent variables/factors which describe the maximum covariance between the spectral information and the reference drip loss values [13]. In this study predictions are validated with full cross-validation (leave-one-out) and for estimating the
correct number of latent factors. The optimum number of factors in the PLS calibration model was defined at the lowest value of the prediction residual error sum of squares (PRESS). The predictive ability of the calibration model was then evaluated by calculating some statistics such as standard error of calibration (SEC), coefficient of determination in calibration, standard error estimated by cross-validation (SECV) and coefficient of determination in cross-validation. All computations and multivariate data analyses were performed with the chemometric software Unscrambler 7.9 (CAMO, Trondheim, Norway) and Matlab 7.7 (The Mathworks Inc., Natick, MA, USA). The main steps of the algorithm developed for analyzing hyperspectral images and visualizing drip loss are shown in Figure 1.

![Figure 1 Main steps of the algorithm developed for analyzing hyperspectral images.](image)

**Selection of Important Wavelengths**

The hyperspectral data have a great degree of dimensionality with redundancy among contiguous wavelengths meaning that some wavelengths are correlated with each other. Usually it is also easier to interpret results if the number of variables is reduced and that is why careful identification of the most informative wavelengths is quite important [14]. Only the most important wavelengths (variables) having the great influence in drip loss prediction should all be kept in the model. In this study, the regression coefficients resulting from the best PLSR prediction model are considered as an indication of the most important wavelengths that does not suffer from redundancy and contribute most in drip loss prediction of the beef samples. Variables (wavelengths) having large regression coefficient values (irrespective of sign) were considered as good candidates for effective prediction.

**Visualization of Drip Loss**

Once the important wavelengths are identified, a new PLSR model was developed using only the spectral data at these particular wavelengths. The new PLSR model was then used to predict drip loss in each pixel of the hyperspectral image. This was carried out by calculating the dot product between spectrum of each pixel in the image and the regression coefficients obtained from the PLSR model. The result of this multiplication extrapolates drip loss in all spots of the sample which facilitates discovering the difference in this property within one sample as well as among the samples of different sources.
RESULTS & DISCUSSION

Spectral Variation among Tested Samples

The main NIR spectral patterns of the tested samples originated from different muscles and different breeds are shown in Figure 2a. The spectral data extracted from a certain sample contains relevant information related to the sample composition. The score plot of the first two principal components (accounted for 95 % of the total variance) is illustrated in Figure 2b. Samples having high drip loss (ST samples) tended to be segregated in one group in the positive side of PC1 meanwhile the samples with the lowest drip loss (mainly PM samples) were located in the negative side of PC1. Samples with intermediate drip loss (belonging to PM and LD muscles) are located in between of these two groups. Figure 5 indicated that the tested samples had reasonable variation in their spectral patterns due to differences in their physicochemical properties including drip loss.

![Figure 2](image.png)

**Figure 2.** Spectral features of the examined samples. a) Mean spectral profiles of the tested muscles, b) score plot of principal component analysis (PCA).

Prediction of Drip Loss

The performance of PLSR model in for prediction drip loss using the full spectral range (Model 1) and the reduced PLSR model using the important wavelengths (Model 2) are shown in Table 1. As epitomized in Table 1, the PLSR both models had a high performance in both calibration and cross-validated conditions.

**Table 1.** Partial least square regression (PLSR) models for predicting drip loss in beef samples by using the full spectral range (Model 1) and by using only the important wavelengths (Model 2).

<table>
<thead>
<tr>
<th>PLSR model</th>
<th>Wavelengths</th>
<th>No. of Latent factors</th>
<th>$R_C^2$</th>
<th>$R_{CV}^2$</th>
<th>SEC (%)</th>
<th>SECV (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Model 1</td>
<td>237</td>
<td>9</td>
<td>0.92</td>
<td>0.89</td>
<td>0.21</td>
<td>0.26</td>
</tr>
<tr>
<td>Model 2</td>
<td>6</td>
<td>6</td>
<td>0.89</td>
<td>0.87</td>
<td>0.25</td>
<td>0.28</td>
</tr>
</tbody>
</table>

Wavelength Selection

According to Wold et al. [15], optimum wavelengths may be equally or more efficient than full wavelengths provided that the wavelengths which carry most information are selected. Locating the best set of wavelengths for predicting particular meat attribute is extremely important to obviate the high dimensionality of the hyperspectral data. Besides saving computation time, working with only important wavelengths (if well selected) leads to more optimized calibration models by avoiding the colinearity among predictors (wavelengths). In this study, wavelengths associated with large regression coefficients of the PLSR model were considered as important wavelengths.

From regression coefficient plot illustrated in Figure 3a, eight individual wavelengths (921, 940, 997, 1144, 1214, 1342, 1443 and 1668 nm) were identified as important wavelengths. Out of these wavelength set, two wavelengths of 927 and 1668 nm at the both edges of the spectrum were excluded due to low signal-to-noise
ratio at both sides of the spectrum. The remaining six wavelengths (940, 997, 1144, 1214, 1342 and 1443 nm) were then used as important wavelengths to replace the full spectral range because they carried the most relevant information of drip loss in the samples. By using these selected six wavelengths, a new PLSR model (Model 2) was established using these wavelengths as the predictors of the drip loss of the beef samples. The predicted values of drip loss of the samples were illustrated in Figure 3b.

Figure 3. (a) Selection of important wavelengths, (b) predicted versus measured drip loss values of tested beef samples using PLSR model (Model 2) of six wavelengths (940, 997, 1144, 1214, 1342 and 1443 nm).

Distribution Map of drip loss

After multiplying the model’s regression coefficients of PLSR model (Model 2) by the spectrum of each pixel in the image, a prediction image (called distribution map) was created that exhibits the distribution of drip loss within the sample. In the resultant distribution map, pixels that had similar spectral features gave the same predicted value of drip loss, which were then visualized in a similar colour in the image. Figure 4 shows examples of distribution maps of some examined samples. Although it was far difficult to figure out the difference in drip loss from sample to sample and from point to point by naked eye, the drip loss difference within and among the samples is very obvious to be discerned from the final distribution maps.

Figure 4. Difference in drip losses among tested muscles. a) Pseudo-colour image of the sample constructed by concatenating different three spectral bands, b) distribution maps of drip loss resulting from Model 2. The number below each sample is the average drip loss of this sample which decreases from left to right (ST = M. semitendinosus, LD = M. longissimus dorsi, and PM = Psoas Major).

As seen in Figure 4, the M. semitendinosus muscles showed the highest drip loss values although there are some samples exhibits small values of drip loss. Even the difference in drip loss from location to location within the same sample could be easily discerned. The fat pixels were also obvious to be recognized in the resulting distribution map since these pixels had no drip loss and were set to a constant value. This approach is very important because it facilitates the assessment of fat flacks distribution if the marbling level need to be estimated in the sample. Moreover, knowing the distribution of water in meat is quite important to reflect
the influence of some processing regimes such as manipulation of the net charge of myofibrillar proteins and the structure of the muscle cell and its components as well as the amount of extracellular space within the muscle itself [4].

CONCLUSION

This study was conducted to investigate the ability of near infrared (NIR) hyperspectral imaging technique for predicting drip loss in fresh beef. On the basis of the results and accompanying illustrations presented in this work, the method suggested was reasonably efficient as a rapid assessment method of drip loss of different beef muscles (ST, LD and PM). In view of meat quality evaluation, these results verified the substantial propensity of this technology to be an excellent alternative to the time-consuming and conventional methods. The capability of the hyperspectral imaging technique to visualize the difference in drip loss in a pixel-wise manner would enable this technology to demonstrate the difference in numerous meat traits from sample to sample or from portion to portion in the same sample. Enhanced refinement of this technique in terms of hardware and software improvements may allow for non-destructive and rapid quality measurements at the processing plants of meat products.

ACKNOWLEDGEMENTS

The authors would like to acknowledge the funding of the Irish Government Department of Agriculture, Fisheries and Food under the Food Institutional Research Measure (FIRM) programme.

REFERENCES