Non-destructive Texture Analysis of Farmed Salmon Using Hyperspectral Imaging Technique

Di Wu, Hong-Ju He, Da-Wen Sun*

The Food Refrigeration and Computerised Food Technology (FRCFT) Research Group, School of Biosystems Engineering, University College Dublin, Agriculture & Food Science Center, Belfield, Dublin 4, Ireland
*Corresponding author. E-mail: dawen.sun@ucd.ie

Abstract
The potential of hyperspectral imaging (HSI) technique coupled with multivariate analysis was evaluated for non-destructively assessing texture of salmon fillets. Hyperspectral images (400 - 1000 nm) were acquired for salmon samples and their spectral data were extracted. Three texture profile analysis (TPA) parameters of hardness, cohesiveness, and adhesiveness were measured for each sample by using an Instron Universal Testing Instrument. Partial least square regression (PLSR) was then applied to establish quantitative models between spectral signatures of samples and their corresponding TPA parameters, resulting in correlation coefficients ($r^2$) of 0.665, 0.555 and 0.606, and root mean square errors estimated by cross validation (RMSECV) of 4.09, 0.067 and 0.504 for hardness, cohesiveness, and adhesiveness, respectively. The results demonstrated that hyperspectral imaging is a potential technique to quantitatively measure texture of salmon fillet in a rapid and non-invasive way.

Key words: Hyperspectral imaging, salmon fillets, principal component analysis, partial least square regression, texture

1. Introduction
Salmon is one of popular seafood products which provide consumers excellent protein, fat and other nutritional components. Salmon industry should deliver products with high quality safety to the marketplace to meet the expectation of consumers. Consumers will like to pay more for prime fillets with high quality. Guaranteeing quality of salmon fillets would increase confidence in customers and promote repeated purchases. To conform to consumers’ expectations on salmon quality, inspections have to be taken throughout the entire process and management system by applying quality control regimes in all phases of salmon business.

Texture is a critical parameter that determines the overall quality perception of salmon products (Morkore & Einen, 2003). Soft flesh leads to reduced acceptability by the consumers and quality downgrading in the salmon processing industry (Morkore & Einen, 2003). Texture depends on the connective tissue, consisting of mainly collagen (responsible for tensile strength) and the myofibrils, consisting of myosin and actin (Casas et al., 2006).

In general, there are two main approaches to measuring the texture of fish flesh: organoleptic assessment using trained taste panels and instrumental methods (Ashton et al., 2010). The first approach is used exclusively in routine assessments of fish, which includes visual examination and hand touch with raw materials (Dunajski, 1979). The intensity or amount of a given property is indicated on 5 or 10 points rating scales. Usually, the panelists are given rating scales with points anchored verbally (Dunajski, 1979). However, the design and execution of taste panels require considerable skill and experience to obtain reliable results (Ashton et al., 2010). Human inspection is subjective, time-consuming, laborious, tedious, and inconsistent. Moreover, only small numbers of fish can be assessed due to the need for panelists to taste multiple pieces of each sample and the high cost of sensory analyses is also often a limiting factor (Ashton et al., 2010). In contrast, texture of salmon fillets may be
measured objectively by using mechanical food testing equipment (Sigurgisladottir et al., 1999). Instrumental measurements of texture are preferred over sensory evaluations since instruments may reduce variation among measurements due to human factors and are more precise (Casas et al., 2006). However, instrumental methods are destructive, time consuming, laborious, costly, and unable for a large number of samples, and require lengthy sample preparation, and therefore cannot be used routinely by the industry. Moreover, measurement of texture gives variation along the salmon fillets from head to tail. Because of the heterogeneity of the fillets, reproducibility of instrumental measurements is affected by sampling technique. Instrumental measurements obtain only the texture values of several sampling points to represent the mean of the attributes for the sampling part or the whole fillet, and thus their measurements are not very representative in heterogeneous materials, especially salmon fillets. The lack of a rapid and objective method of non-invasively inspecting based on quality and safety attributes of salmon fillets has seriously limited the ability of the salmon industry to provide consumers with products of consistent quality and safety.

Recently, optical sensing technologies such as spectroscopy and imaging have been investigated as potential tools for the above purpose. Spectroscopy is a widely recognized technique for quality inspection based on the measurement of optical properties of food products (Cen & He, 2007). Various works successfully realized the measurement of chemical compositions of fish products by using spectroscopy technique (Huang et al., 2002; Xiccato et al., 2004; Folkestad et al., 2008), however there is a lack of knowledge on the concentration gradients and spatial distributions of these quality attributes in these works, because the spectral measurement focuses only on a round area of the sample being analyzed. On the other hand, measurement of the spatial features of food products can be achieved by conventional imaging system or more specifically computer vision with the minimum of human intervention (Du & Sun, 2006). However, because operating at visible wavelengths in the forms of monochromatic or color images, a conventional imaging system is incapable in inspecting specimens with similar color, classifying complex objectives, predicting internal attributes (e.g. chemical components) that are less relevant to colour, and in detecting invisible defects.

With the integration of the main advantages of conventional spectroscopy and imaging technique, hyperspectral imaging (or imaging spectroscopy) has been emerged as a potential tool for non-destructive evaluation and inspection of food quality and safety (ElMasry et al., 2008; Taghizadeh et al., 2009; ElMasry et al., 2011, 2012; Wu et al., 2012). Hyperspectral image acquired by the technique provides much more information of tested samples than existing spectroscopy or imaging because of its capacity of offering both spectral and spatial characteristics simultaneously, which can be used to analyse and characterize the physical and/or chemical attributes of examined products. Particularly for salmon, Segtnan et al. (2009a) determined fat distribution in raw and salted salmon fillets and obtained good results with r of 0.947 for raw fillets, 0.966 for salted fillets, and 0.958 for the sample set of both raw and salted fillets. Ottestad et al. (2009) analyzed the average ice fraction and fat as well as their spatial distribution in super-chilled salmon fillets. Good r² of 0.96 and 0.92 were obtained for the prediction of ice fraction and fat, respectively. Segtnan et al. (2009b) found that hyperspectral imaging was also able to determine NaCl contents within salted salmon fillets with r=0.86. To our knowledge, no research endeavors have been reported yet for characterizing texture of salmon or other fish using hyperspectral imaging technique. Therefore, it is of our interest to implement hyperspectral imaging for the texture inspection of salmon fillets.

Given the limited information on the application of hyperspectral imaging systems used for evaluating texture of salmon fillets, the major objective of this study was to investigate the potential of using hyperspectral imaging technique in the spectral range of 400 – 1000 nm as a rapid and non-invasive tool for assessing texture distribution of salmon fillets. Hyperspectral data was extracted and analysed by partial least square regression (PLSR),
and prediction models were established between hyperspectral images and reference texture parameters (Hardness, Cohesiveness, and Adhesiveness) estimated by texture profile analysis (TPA) instrument.

2. Materials and Methods

2.1 Samples preparation

Three groups (24 fillets in all) of fresh farmed Atlantic salmon fillets (Salmo salar) were purchased from local supermarkets in Dublin, Ireland. In specific, ten fillets were from Scotland, eight fillets from Norway, and six fillets from Ireland. The salmon fillets were fresh and of superior quality. The fillets were labeled and then transported to laboratories of Food Refrigeration & Computerized Food Technology (FRCFT), University College Dublin (UCD), Ireland. Each fillet was first scanned by the hyperspectral imaging system and then its reference value of colour was determined using the colourimeter method explained below.

2.2 Hyperspectral imaging system

A pushbroom line-scanning HSI instrument (DV Optics Ltd., Padua, Italy) was used in this study for the acquisition of hyperspectral images of each fillet. The system mainly consisted of Specim V10E spectrograph (Spectral Imaging Ltd., Oulu, Finland) covering the spectral range of 400–1000 nm (spectroscopic resolution of 5 nm), a high performance CCD camera (Basler A312f, effective resolution of 580×580 pixels by 12 bits), an objective lens (25mm focal length), an illumination source (150W halogen lamp source attached to a fibre optic line light positioned at an angle of 48° to the moving table), a mirror, a moving table, an computer system equipped with an acquisition software (Spectral Scanner, DV Optics, Padua, Italy). Each fillet was placed on the moving table and then was scanned line by line.

2.3 Subsampling for reference analysis

An appropriate span of attribute values in the calibration samples is important for the development of the calibration model (Berzaghi & Riovanto, 2009). On the other hand, texture can vary a lot within the same fillet, and local colour could be much different from the mean colour of the whole fillet (Sigurgisladottira et al., 1997). Therefore, subsampling was carried out to provide wide variation in colour for the development of the calibration model. Each salmon fillet was cut into rectangular shapes with dimensions of 2 × 2 × 1.5 cm at different locations, resulting in a total of 120 subsamples for texture profile analysis (TPA).

2.4 Measurement of texture parameters

Three TPA parameters involving hardness, cohesiveness, and adhesiveness were measured by an Instron Universal Testing Instrument (Model 4411, Canton, Mass., U.S.A.) at room temperature (20 °C). The reference values of these texture parameters measured at different locations of salmon fillets were presented in Table 1.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Max</th>
<th>Min</th>
<th>Mean</th>
<th>Standard deviation</th>
<th>Range</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hardness</td>
<td>29.13</td>
<td>2.21</td>
<td>10.97</td>
<td>5.46</td>
<td>26.92</td>
</tr>
<tr>
<td>Cohesiveness</td>
<td>0.71</td>
<td>0.27</td>
<td>0.52</td>
<td>0.08</td>
<td>0.43</td>
</tr>
<tr>
<td>Adhesiveness</td>
<td>3.45</td>
<td>0.24</td>
<td>1.60</td>
<td>0.63</td>
<td>3.21</td>
</tr>
</tbody>
</table>

2.4 Reflectance calibration and images acquisition

Two extra images acquired for dark (D) and standard white (W) references were used in order to eliminate the effects of illumination and detector sensitivity and geometry. The dark image was acquired and recorded by turning off the light source and completely covering the camera lens with its cap. The white image was obtained by collecting a response from a uniform white calibration tile. The calibrated reflectance value (C) was calculated from the raw signal (R) by the following formula:
\[ C_i = \frac{R_i - D_i}{W_i - D_i} \]

where \( i \) is the pixel index, i.e. \( i=1,2,3...,n \) and \( n \) is the total number of pixels within the region of interest (ROI).

After reflectance calibration, hyperspectral images of all salmon fillets were acquired by the hyperspectral imaging system equipped with data analysis software.

2.5 Identification of region of interest (ROI) and spectral data extraction

The Region of Interests (ROI) Function of ENVI v4.6 software was used to isolate the subsample from the fillet, resulting in conducting spectral data extraction from each subsample in the hyperspectral image. The whole isolation process was executed manually. The isolated region had the same position and size of the subsample whose TPA was measured by the Instron instrument. After identification of ROIs, the mean spectrum of each ROI was extracted.

2.6 Multivariate data analysis

In this study, partial least square regression (PLSR) was used to establish quantitative models between spectral and TPA parameters. PLSR is a frequently used chemometric method in the calibration of a multivariate spectral model with explanatory or predictive purposes (Gerlach et al., 1979). It is suitable in the application that there is a large amount of correlation, or even colinearity in X-variables, such as the spectral data. For the analysis of hyperspectral image data, the calibrated quantitative model should be evaluated for its performance by validation process. In this study, leave-one-out cross validation (LOOCV) was used for the validation purpose.

3. Results and Discussion

3.1 Spectral features of salmon fillets

The extracted mean spectral features of the tested salmon fillet originated from different farm locations are shown in Fig. 1. Spectra have low reflectance at around 500 nm and high reflectance at 650-700 nm, which cause salmon fillet red colour. There are some broadband peaks in the spectral profile of salmon fillet. In specific, local absorption peaks appeared at 760 nm (O-H stretching third overtone) and 970 nm (O-H stretching second overtones) were due to the presence of water in the sample.

3.2 PLSR model using full wavelengths

Fig. 1 indicates that there was no feature peaks of TPA parameters for the reflectance spectral profiles of salmon samples in 400-1000 nm range. Therefore, full spectral range was first considered for establishing the prediction model of TPA parameters using PLSR. In addition, when more samples were considered, the spectral patterns of the examined samples were various, which required chemometrics for the data mining, instead of analysing spectral profiles using naked eyes.

In this study, the prediction of TPA parameters was conducted by using PLSR to establish the quantitative relationship between the matrix (X) with the extracted reflectance spectral data within full spectral range (121 independent wavelength variables) and the column vector (Y) with one of their corresponding dependent variables (hardness, cohesiveness, and adhesiveness). Table 2 shows the results of calibration and cross-validation statistical parameters of PLSR models developed using the full spectral range for predicting hardness, cohesiveness, and adhesiveness of the tested salmon samples.

With the 121 variables and full-cross validation, the prediction results for hardness, cohesiveness, and adhesiveness obtained with correlation value (R_C) of 0.734, 0.648 and 0.727 and root-mean-square errors of calibration (RMSEC) of 3.689, 0.060 and 0.432 for calibration process (R_C), correlation value (R_CV) of 0.665, 0.555 and 0.606 and root-mean-
square errors of cross-validation (RMSECV) of 4.09, 0.067 and 0.504 for validation process, respectively. Although the results were not very good, it should be noticed that another research found no prediction of TPA parameters was possible based on the spectra in the range of 400-1100 nm (Isaksson et al., 2002). The reason of our improvement may be that the spectra of specific regions for the TPA determination were exacted according to the spatial information of hyperspectral images. The capability of hyperspectral imaging to quantitatively determine the texture of salmon fillet would enable this technology to be used in automatic inspection of fish quality, which would result in a decrease of overall production cost, removing human subjectivity and inconsistency, and saving time.

Table 2 Performance of PLSR models for predicting colour (L*, a*, and b*) of salmon.

<table>
<thead>
<tr>
<th>TPA</th>
<th>No. of latent variable</th>
<th>Calibration</th>
<th>Cross-validation</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>r_C</td>
<td>RMSEC</td>
</tr>
<tr>
<td>Hardness</td>
<td>8</td>
<td>0.734</td>
<td>3.689</td>
</tr>
<tr>
<td>Cohesiveness</td>
<td>8</td>
<td>0.648</td>
<td>0.060</td>
</tr>
<tr>
<td>Adhesiveness</td>
<td>11</td>
<td>0.727</td>
<td>0.432</td>
</tr>
</tbody>
</table>

4. Conclusions

Hyperspectral imaging system in the region of 400-1000 nm was investigated to assess three TPA parameters of salmon fillets. On the basis of the results and accompanying illustrations presented in this work, the study demonstrated the ability of the method based on hyperspectral imaging to measure texture of salmon fillets. This method was a rapid, contact-free, and consistent evaluation, and can be used as a reliable alternative to traditional universal testing machines for texture of salmon fillet.

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References


FIGURE 1: Extracted mean spectral features of the salmon fillet in the spectral range of 400-1000 nm