

Detection of beef aging combined with the differentiation of tenderloin and sirloin using a handheld NIR scanner

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Abstract There is an expressed need for non-destructive user-friendly tools that can help customers and various stakeholders of the food market to identify and qualify samples rapidly and accurately. The identification of high quality meat cuts and the determination of aging are important challenges where handheld near infrared spectroscopy can provide perfect solutions. The objective of this study was to develop multivariate models for differentiation of beef cuts and prediction of the aging time based on the NIR spectra acquired with a handheld Tellspec Enterprise Food Sensor. Sirloin and tenderloin samples were stored at 4°C in plastic bags for 10-day period during two experiments, and spectra were recorded daily. The investigated sirloin and tenderloin samples were separated in principal component analysis, and it was possible to use the principal components in a supervised classification (linear discriminant analysis) to build model on meat authentication. 85.37 % of the sirloin and tenderloin samples were classified correctly in independent validation tests. Multivariate calibration on aging was developed for the separate meat types. After omitting the first and last days of the experiments, accurate calibration models were built on the aging of beef samples. Accordingly, 1.1 or 1.5 days of precision was achieved during independent predictions for aging time of sir-

loin or tenderloin, respectively. Our results proved that the Tell-spec Enterprise Food Sensor provides the possibility for rapid and non-destructive determination of meat type and stage of aging.

Keywords: Portable, near infrared spectroscopy, meat, classification, calibration, storage.

1 Introduction

The quality of beef highly depends on the cut [1] and aging time [2]. Consumers are willing to buy valid product of known origin if it has special palatability or nutritional merit, even if it has a higher price [3]. Among other motives, the high commercial value of meats which are more valued by consumers leads to an expressed need for fast, accurate and objective methods to identify the different types of meats by species and cuts, and to determine the post mortem aging time. Near infrared (NIR) spectroscopy as a cost effective analytical method is widely used in food industry for measurement of quality attributes. The NIR technique is a rapid and non-destructive method requiring little or no sample preparation, still, it provides high accuracy in many applications. Contrary to wet chemistry, no reagents are required and no waste is produced. The first application of NIR technique to detect properties of meat was reported five decades ago [4], and thirty years later on-line applications were developed for food industry [5]. NIR spectroscopy is among the most progressive methods frequently used for qualitative and quantitative analyses of various meats [6]. Nowadays, the miniaturized NIR spectrometers are used in many fields of research, however, there is still a vast need for simple low cost NIR instruments usable by non-technical personnel in everyday situations. The goal of the present study was to develop multivariate models for differentiation of different beef cuts and prediction of the aging time based on the NIR spectra acquired with a handheld scanner.

2 Materials and methods

Twelve slices of beef tenderloin ($n = 6$) and sirloin ($n = 6$) were stored at 4°C in sealed plastic bags over a 10-day period (Fig. 3.1). Meats



Figure 3.1: (a): Beef tenderloin; (b): sirloin samples of the experiment 1, prepared for storage.

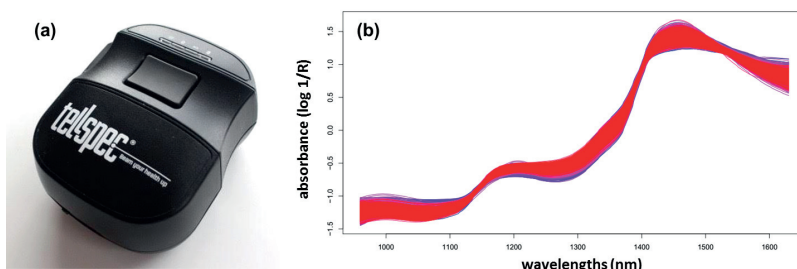


Figure 3.2: (a): The Tellspec Enterprise Food Sensor handheld NIR spectrometer; (b) the acquired spectra ($n = 600$) of tenderloin and sirloin samples of experiment 1.

were purchased from a Hungarian slaughter house, slices were cut and packed right after dissection, following a 24 hours post slaughter chilling. The experiment was performed twice with one month difference (experiment 1 and experiment 2) in order to validate the quantitative and qualitative NIR models using independent data (total $n = 24$).

The NIR spectrum of each slice was acquired through the plastic bag, using a Tellspec Enterprise Food Sensor (Tellspec Inc., Toronto, Ontario, Canada) (Fig. 3.2a). Spectra of each slice were recorded daily with 2 nm spectral step in the 950–1630 nm spectral interval, using the Tellspec application for mobile devices. Figure 3.2b shows the raw

spectra of experiment 1 ($n = 600$). Various sample pre-processing methods and multivariate data analysis techniques were used to process the spectral data [7]. Principal component analysis (PCA) was used to detect spectral outliers and describe the multidimensional pattern of the dataset [8]. Supervised classification models were built with linear discriminant analysis (LDA) to perform pre-defined grouping of tenderloin and sirloin samples based on the spectral properties [7]. Partial least squares regression (PLSR) was used to develop NIR calibration models on the aging [9]. Cross-validation was used for optimization of the models, when data of single days were left out of the calibration and were used for validation, iteratively. Independent validation was applied between the two experiments when models of one experiment were tested with the data of the other experiment. Data processing and evaluation was done with the R Project (www.r-project.org).

3 Results and discussion

Considerable spectral difference was observed between the NIR spectra of tenderloin and sirloin, and according to aging of the meat samples. Daily NIR data (smoothed and normalized) were evaluated with PCA to see the spectral differences of the two meat cuts. PCA score plot of Fig. 3.3a shows the separation of tenderloin and sirloin samples on one day. The separation is along PC1 that describes 92.5 % of the total spectral variation. PC1 loading was dominated by fat (C-H) absorption region around 1210 nm, showing the differences in intramuscular fat content of the two meat types. NIR data of the whole experiments were evaluated with PCA to check the spectral variation according to aging. Figure 3.3b shows the PCA score plot of the sirloin samples of experiment 1. Colors indicate the date of aging (from red to blue), showing that PC2 covering 17.8 % of total spectral variation highlights the spectral regions changing considerably during aging. PC2 loadings highlighted water absorption bands in 1380 and 1450 nm regions showing the changes of water structure.

The separation of the two cuts in the PCA score plot considering the whole dataset of experiment 1 is shown in Fig. 3.4a. The PCA scores were used as input variables to build the LDA models providing orthogonal variables for identification of sirloin or tenderloin spec-

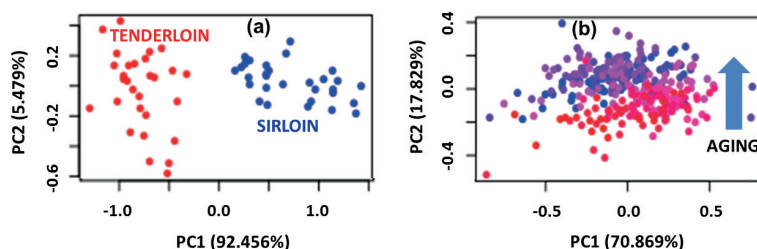


Figure 3.3: (a): PCA score plot showing data of one day with a clear separation of the tenderloin and sirloin samples along PC1; (b): PCA score plot of the sirloin samples of experiment 1 showing the trend of aging along PC2.

tra. The models were calculated on one of the two experiments and were tested with the data of the other experiment (Fig. 3.4b). The ratios of the correctly classified samples during the LDA model building processes were 93.55 % and 93.23 % for experiment 1 and experiment 2, respectively. The hit ratios of the two validation tests of the LDA models were 83.76 % and 86.97 %, respectively.

The PLSR calibration models on aging were prepared with sirloin and tenderloin spectra separately. Models were trained on one of the two experiments applying cross-validation based optimization where one day's data were left out iteratively, and spectra of the other experiment were used for independent predictions to validate the model. More accurate predictions were achieved for sirloin then for tenderloin. The root mean square error of prediction (RMSEP) was less than 2 days for sirloin, and 2.5 days for tenderloin. As Fig. 3.5 shows, non-linear change of the meat samples was observed during aging. Accordingly, PLSR models were built on the middle of the investigated period (2-9 days), and average accuracy (RMSEP) of the independent predictions improved to 1.13 days for sirloin and 1.48 days for tenderloin (Fig. 3.6).

4 Conclusions

The aging and the type of the meats have significant effect on the NIR spectra recorded with the handheld Tellspec Enterprise Food Sensor.

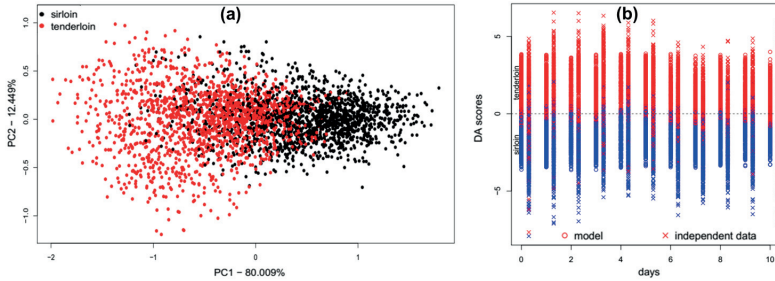


Figure 3.4: (a): PCA score plot of the beef spectra recorded in experiment 1, showing the difference of sirloin and tenderloin along PC1 that describes 80 % of the total spectral variation; (b): results of the classification of sirloin and tenderloin samples when the LDA model was built on the spectra of experiment 2, and it was validated with 86.97 % hit ratio using the independent samples of experiment 1.

The investigated sirloin and tenderloin samples were separated based on the spectral information related to C-H bonds, i.e. intramuscular fat. It was possible to use the principal components in a supervised classification to build model on meat authentication. 85.37 % of the sirloin and tenderloin samples were classified correctly in independent validation tests. Meat type has bigger effect on the NIR spectra when compared to the effect of meat aging, thus, it is reasonable to calibrate on aging within the separate meat types (sirloin or tenderloin). Due to the non-linear changes of meat during the aging process, it was possible to achieve calibration models on meat aging with an accuracy of 2 or 2.5 days for sirloin or tenderloin, respectively. To decrease the non-linearity, calibration models were built after omitting the initial and final days of the experiments. This resulted 1.1 or 1.5 days of precision during independent prediction for aging time of sirloin or tenderloin, respectively. Our results proved that the Tellspec Enterprise Food Sensor provides the possibility for rapid and non-destructive determination of meat type and days of storage, i.e. stage of aging.

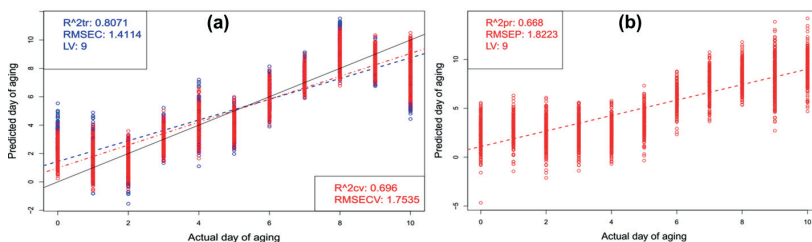


Figure 3.5: (a): Calibration (blue) and cross-validation (red) results of the PLSR model prepared on aging days of sirloin samples of experiment 2; (b): prediction results of the above mentioned PLSR model when sirloin samples of experiment 1 were used as independent sample set. ($R^2_{tr/cv/pr}$: coefficient of determination in calibration training/cross-validation/independent prediction, RMSEC/RMSECV/RMSEP: root mean square error of calibration/cross-validation/prediction, LV: number of latent variables).

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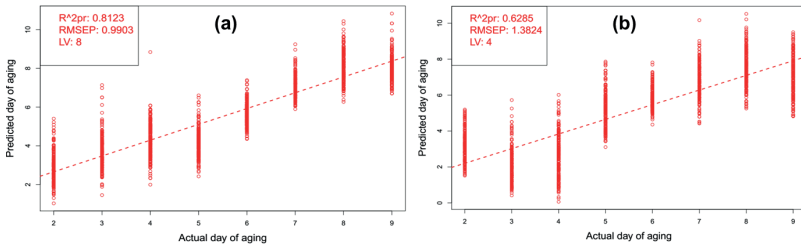


Figure 3.6: Independent prediction of aging days of the (a) sirloin and (b) tenderloin samples of experiment 2 using PLSR models trained on the NIR data of the sirloin or tenderloin samples of experiment1, respectively. (R^2_{pr} : coefficient of determination in prediction, RMSEP: root mean square error of prediction, LV: number of latent variables).

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