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ON-LINE ANALYSIS OF THE PROXIMAL COMPOSITION OF WHOLE ENTRECÔTES (CHUCK ENDS) BY A NIR TRANSFLECTANCE INSTRUMENT - A PRELIMINARY REPORT

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Introduction

Un-processed meat raw materials are heterogeneous with regard to distribution of the major constituents, i.e. moisture, fat and protein. In reflectance spectroscopy, where the surface of the sample is monitored, good estimates of the chemical composition of such commodities are not easy to obtain. The surface to measure is limited, and frequently this surface does not represent the average contents of the constituents of interest.

NIR has in the last two decades found many applications in food analysis. However, the NIR sampling step has often proved critical [1]. There are three basically different ways of obtaining NIR spectra from a sample: I) By reflectance measurements, where the energy reflected mainly from the surface of the sample is detected. II) By transmittance measurements, where the energy that has been transmitted through the sample is detected. III) By transflectance measurements, which is a combination the two above. The illumination and detection take place on the same side of the sample, like in reflectance measurements, but the energy has been transported some distance into the sample and back to the surface prior to the detection.

NIR reflectance measures mainly the surface and is normally not well suited for measuring heterogeneous samples such as high fat beef cuts. Transmittance measurements, where the total samples can be monitored by NIR, are a better solution for analysis of such small heterogeneous samples. However, for on-line purposes, transmittance measurements pose problems as sample thickness varies and gives rise to undesirable offset variations in the spectra. Many products are also too thick to trans-illuminate. Another possibility is NIR transflectance analysis, where the light probes deeper into the material as compared to reflectance, and a more representative sampling is obtained.

Normally, transflectance measurements require contact between the sample and the instrument probe. This can introduce difficulties, both with regard to mechanics and hygiene in its practical use. However, a new instrument has recently been patented, that measures in remote transflectance with no sample contact.

Objectives

The objective of this study was to explore the potential of a newly developed transflectance NIR instrument in on-line estimation of the proximal composition of whole meat cuts. Entrecôte (corresponds to chuck end) was chosen as a suitable model. Entrecôtes are highly heterogenous beef cuts, with a variation in fat content that makes it interesting for the abattoirs to be able to sort them.

Methodology

40 entrecôtes (chuck end) were sampled from a commercial slaughter house. Each muscle was scanned on a conveyer belt at 4°C for about 6-8sec on both the fat and the lean side. The whole entrecôtes were ground and mixed and 300g from each sample was homogenized in a mini-chopper with horizontal mounted knives for up to 1min. The following analyses were done in duplicates;

- Fat (Soxtec extraction) - AOAC 991.36
- Water (drying overnight at 102-105°C for 16-18hrs) - NMKL 23 (1991)
- Protein (Kjeldahl) – AOAC 981.10 (1983)

The transflectance NIR scanner is an on-line measurement system, modified from a commercial system used for automatic plastic waste sorting (Titech Visionsort, Norway). It is very fast and can measure and analyze objects on a conveyor belt at a high speed (3 m/sec). It is also a spectral imaging system, which produces images with a NIR spectrum in each pixel of the image.

A powerful illumination line was projected down onto samples on the conveyor belt. A vertical black shield protected the detector from the main part of the direct reflected light. Adjusted optics enabled measurement of light emerging from the samples approx. 2cm from the illumination line. This means that both the surface and the interior of the sample were being measured simultaneously. The average NIR spectrum from each image was used for calibration. Measurements on the fat and lean sides of the cut were analyzed both separately and in combination.

The prediction models for each constituent were calculated by partial least squares methods (PLS) and validated by full cross validation. The prediction results were presented as root mean square error of cross validation (RMSECV):

$$RMSECV = \sqrt{I^{-1} * \sum_{i=1}^{I} \left(y - \hat{y} \right)^2}$$

where the sample number is represented by i [1,2,3,..,I], while y and ŷ represents the reference method value and the NIR predicted value, respectively. The PLS regression results for the on-line data were calculated using the software Unscrambler®, version 9.1, (Camo AS, Oslo, Norway).

Results & Discussion

To obtain wide ranges of fat (3.5-26.6%), protein (16.0-21.1%) and water (54.0-74.3%) contents, a broad range of weights of the muscles was obtained in the sampling (1.2-6.1kg). Plotting the content of fat against the contents of water and protein in the cuts showed high correlations, as could be expected (Figure 1). The sums of the components for each sample were checked to trace any outliers.

In Figure 2, an image with an averaged NIR spectrum in each pixel is shown. Fat and lean areas of the surface can easily be identified. Earlier studies on cheese and fish have shown that the penetration depth is as great as 15-40mm, all depending of product. Figure 3 indicates that the penetration of visible light into the cut, from the fat side, is at least 2-3cm. The penetration depth in the wavelength region 800-1000nm is known to be even higher than that of the visible range.

Table 1 gives an overview of the prediction results for fat, water and protein on a set of 39 samples, both vacuum packed cuts and cuts and without package. When scanning on both sides, the average scans were used in the models. Due to the limited number of samples, no more than five factors were allowed in the prediction models. One sample was deleted from the original sample set of 40.

Generally the prediction results for water was better than for fat content. The models for protein were not satisfactory. As expected, un-packed meat yielded improved predictions over packed, but the difference was not large. Scanning both sides of the cut yielded better predictions than scanning only one side, and scanning the fat side gave better prediction results than scanning the lean side.

In Figure 4 the PLS prediction results are presented for fat analysis (39 samples) of un-packed cuts, when both sides are scanned. The correlation coefficient is 0.89 and the RMSECV=2.56%. For water estimation the correlation coefficient and RMSECV improved to 0.91 and 2.01%, respectively (Figure 5).

In the NIR analysis, fat, water and protein were measured simultaneously. The information in the strong relationships between the components is obviously used in the calibrations, which is shown in the similarity of the regression coefficient plots for the components (Figure6). The plot for water and protein are almost identical, while the fat plot is the inverse image of those. This means that the estimations of the individual components are not independent. I.e. a calibration that is developed for muscle meat with a fixed relationship between fat and water can therefore not be used for meat where the ratio between water, fat and other ingredients has been altered 2.

Conclusions

Promising prediction models were observed. Cross-validated partial least square regressions showed that the prediction results for water content was better than for fat content. The models for protein were not satisfactory. As expected, measurements on un-packed meat yielded improved predictions over packed, but the difference was not large. Scanning both sides of the cut yielded better predictions than scanning only one side, and scanning only the fat side gave better predictions than scanning only the lean side. The best models yielded explained variances of approx. 90%, while the cross-validated prediction errors were 2.0-2.5%.

References

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Tables and Figures

Figure 1. Relationships between fat, water and protein (+SUM) in the entrecôtes.

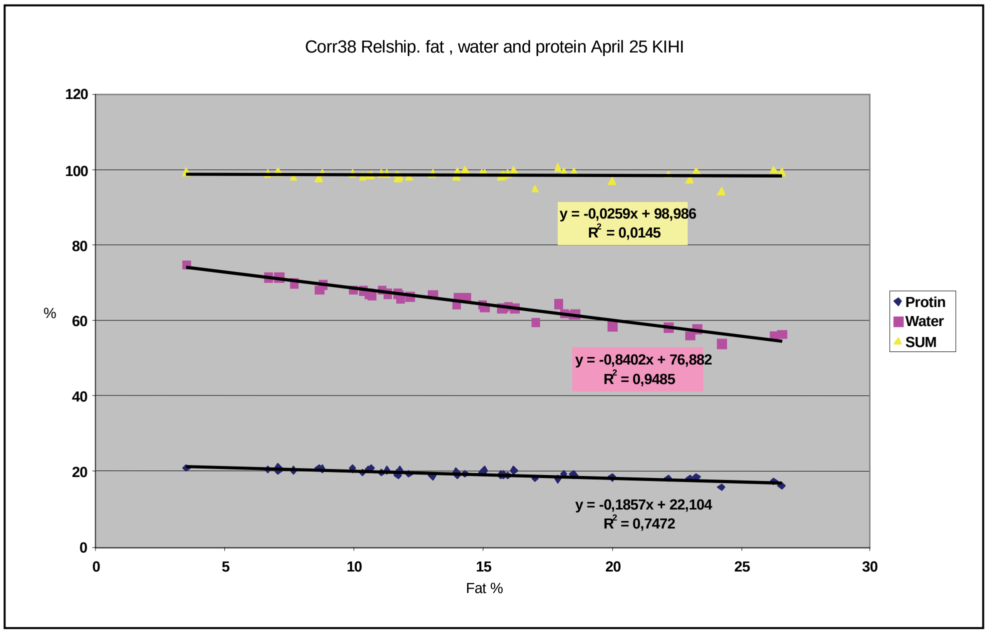
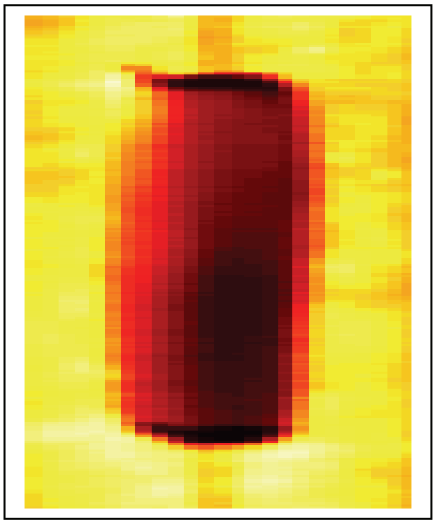


Figure 2. Spectral images of entrecôte (Titech



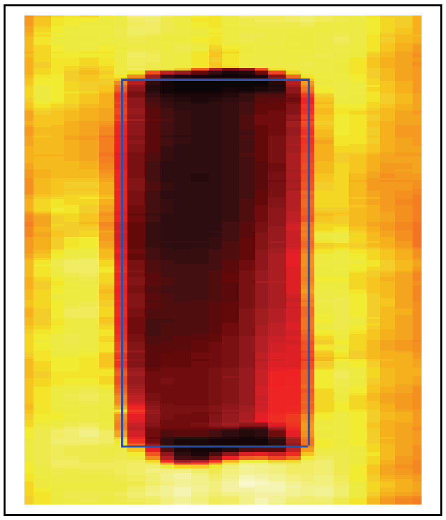


Figure 3. Entrecôte measurement from fat side (Titech Visionsort)

Table 1. Prediction results on- line NIR analysis of proximal composition of whole beef

Measuring mode	Packaging	Meat constituent	Correlation coeffcients	RMSECV %	No of PC's in PLS models
Both sides	Packed	Fat	0.83	3.12	4
		Water	0.85	2.52	5
		Protein	0.61	0.96	3
	Un-packed	Fat	0.89	2.56	5
		Water	0.91	2.01	5
		Protein	0.69	0.88	5
Fat side	Packed	Fat	0.78	3.50	2
		Water	0.79	2.96	5
		Protein	0.62	0.95	2
	Un-packed	Fat	0.86	3.38	4
		Water	0.87	2.77	5
		Protein	0.66	0.92	5
Lean side	Packed	Fat	0.72	3.92	4
		Water	0.70	3.45	4
		Protein	0.57	0.99	2
	Un-packed	Fat	0.73	3.84	4
		Water			
		Protein	0.63	0.93	2

Figure 4. Prediction of fat content (samples scanned both sides, unpacked cuts) (Titech Visionsort)

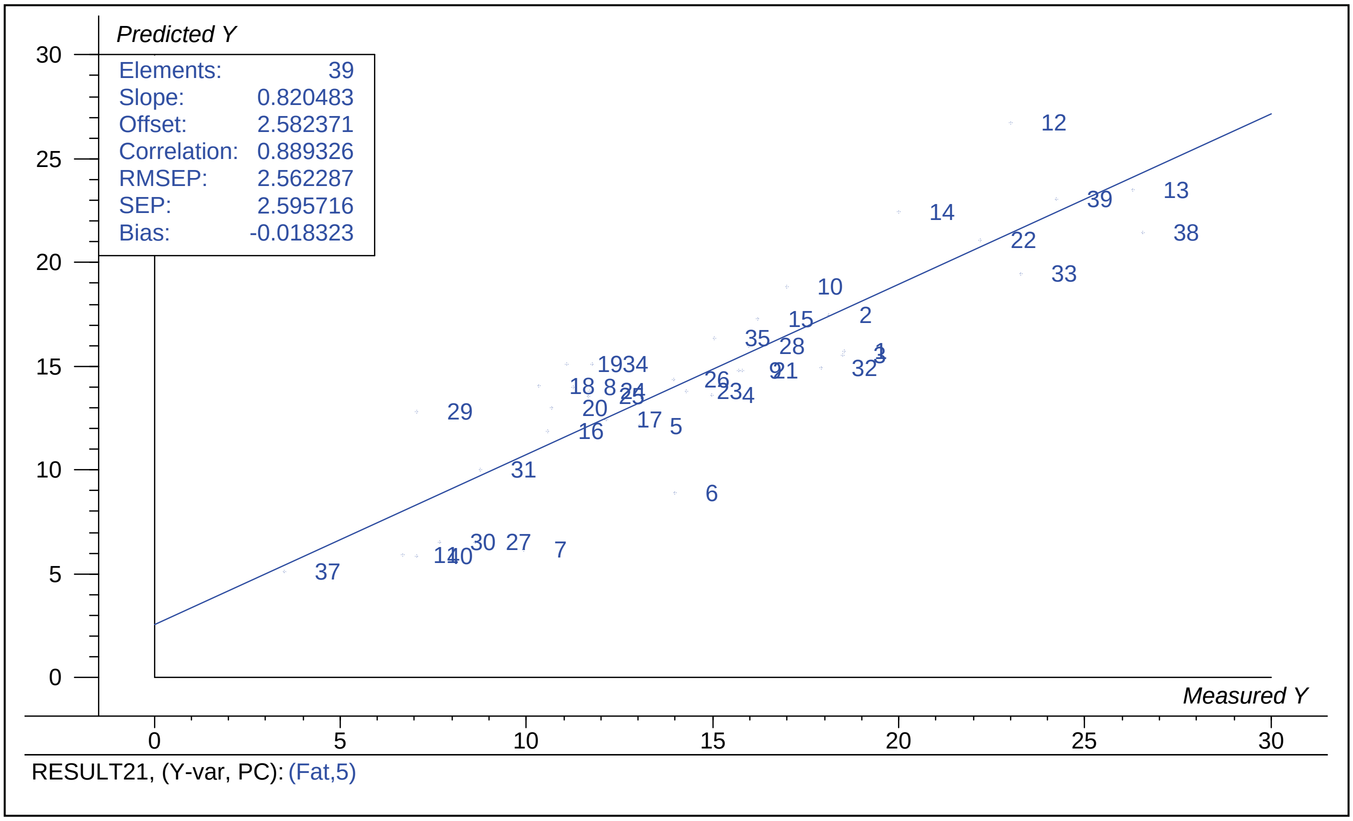


Figure 5. Prediction of water content (samples scanned both sides, un-packed cuts) (Titech Visionsort)

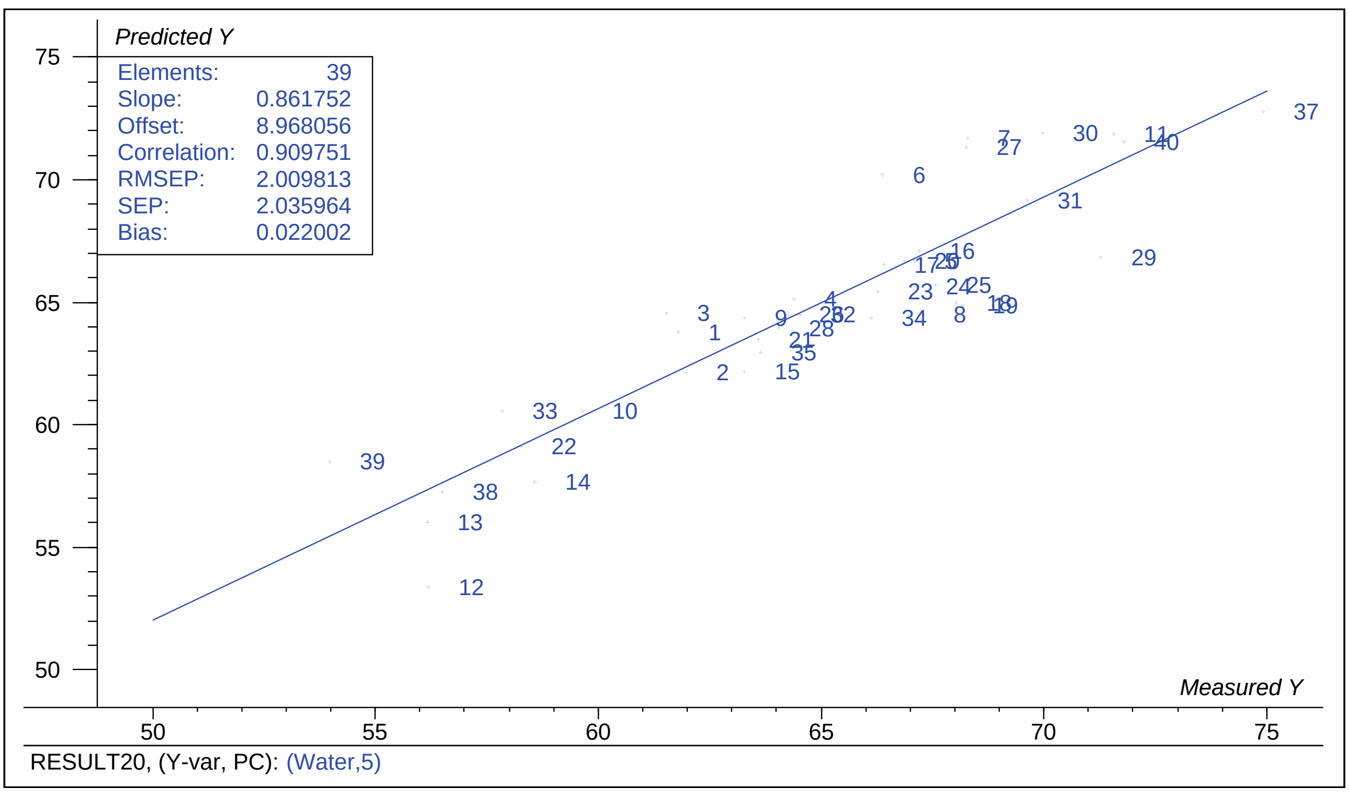
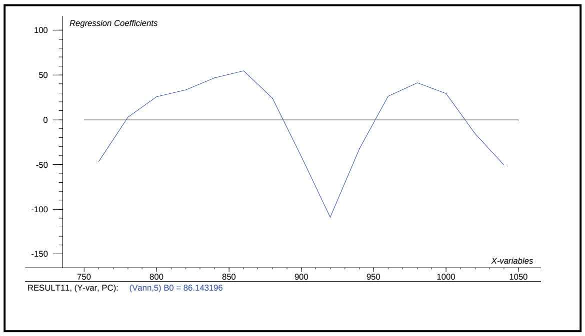
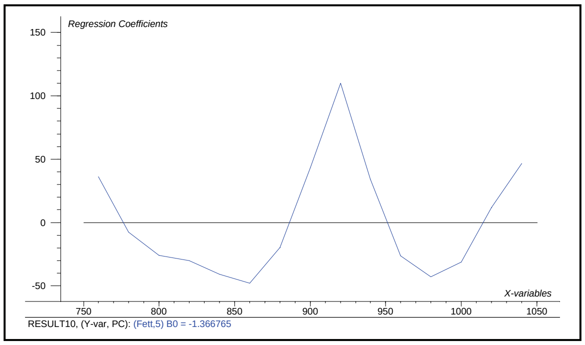


Figure 6. Regression coefficients in PLS- models (samples scanned both sides,

Fat



Water



Protein