Monitoring water content using multispectral imaging and NIR in a minced meat preparation process

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Introduction

Online quality inspection of food process control is today often done by human expert operators who have many years of experience. However, the trend seems to point towards fast non-invasive inspection methods, such as near infrared (NIR) technology for quality inspection in different food process control tasks, as either replacement for, or supplement to the human operators.

We are investigating the potential of using multispectral imaging in the visible as well as the NIR area of the electromagnetic spectrum instead of human operators and as an alternative to standard NIR measurement methods. A drawback of spectroscopic methods is its one dimensional nature. A spectroscope measures everything within its field of view as an average measurement over the area registered by the measuring device. By employing imaging instead of point measurements it is possible to record much larger spatial areas, and thereby gain spatial as well as spectral information. This makes it possible to assess chemical as well as spatial quality features at-line, such as water content, surface color, fat content, particle sizes, texture etc.

In this study, we are specifically investigating the ability of a multispectral camera to predict the water content in minced meat after it has been processed in a continuous frying process at different times and temperatures. Other similar investigations have been done.[1] The camera used is called a VideometerLab,[1] and records multispectral images in a set of predefined wavelengths.

Some absorption bands of water lies in the vis and NIR area around 640 nm, 752–756 nm, 960 nm and 1152–1160 nm. VideometerLab overlaps a large part of this region, which is what we want to utilise to quantify the amount of water in the surface of fried minced meat, by correlation to dry-matter measurements of the same sample.

1 http://www.videometer.com

Experimental setup and data

The study subject of this paper is minced beef with 15–18% fat. The meat was purchased through a wholesale supplier, Inco Danmark a.m.b.a, Copenhagen in a frozen state. The meat blocks of approximately 2 kg. were stored at –30ºC. For the experiment the meat blocks were crushed with a hammer in coarse pieces below 200 g. A portion of about 1 kg was chopped in an industrial meat chopper (Kilia 0.57 m diameter) at the lowest speed step, to prevent heating. The chopping was continued (about 2–3 min.) until the frozen meat was disintegrated with no large lumps left.

Of the disintegrated, still frozen meat, 800 g was fed in consecutive portions of 100 g each to a continuous frying machine at pre-selected temperatures and frying times. Samples were prepared at the temperatures 200ºC, 225ºC and 250ºC; the frying time varied from 120 s to 240 s in 40 s intervals.

The actual water content was determined using a standard dry-matter method (oven drying at 105ºC for 24 h) where the mass of evaporated water of the samples (about 2 g each) was measured by weighing. All measurements were done in triplicate to get more stable measurements, where the mean of the three replications is seen in Table 1.

Standard deviations of the replicates were estimated between 0.18 and 0.42.

The multispectral images were acquired using a VideometerLab, see Figure 1, which records 18 different reflectance spectra corresponding to the wavelengths; (430 nm, 450 nm, 470 nm, 505 nm, 565 nm, 590 nm, 630–645 nm, 660 nm, 700 nm, 850 nm, 870 nm, 890 nm, 910 nm, 920 nm, 940 nm, 950 nm and 970 nm).

The VideometerLab uses an LED technology, which means that no filtering of the incoming light is needed. Furthermore, the camera is equipped with an integrated sphere coated with a matte material, which ensures uniform lighting, avoids highlights and makes it easy to optimise the dynamic range in low contrast areas. VideometerLab technology is a low cost way of acquiring multispectral images since it uses standard silicium chip technology.

For the entire experiment, only the longest 8 wavelengths, the NIR channels, were used for the analyses, in order to avoid e.g. confounded variables in the data modeling.

Table 1. Water Content determined by the dry-matter method.

	200º	225º	250º
120 s	54,32 %	53,17 %	51,01 %
160 s	52,66 %	53,96 %	46,29 %
200 s	51,49 %	52,55 %	49,70 %
240 s	51,16 %	51,27 %	48,28 %

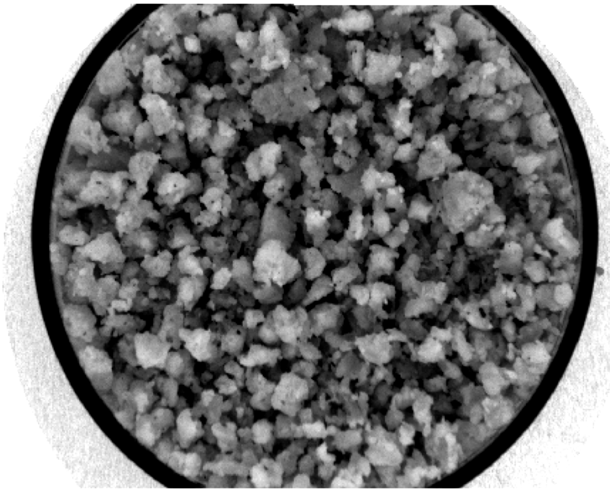

Figure 1. 850 nanometers: unprocessed image.

Data analysis

Having a set of 8 NIR images measured between 850 and 970 nanometers (both included), with corresponding pixels, leads to application of multivariate and chemometric methods. Before applying a multivariate method and calibrating the water system, an expansion of the multispectral images was done. All possible ratios of all eight NIR wavelengths were derived in order to find better features to describe the water content of the sample. The new multispectral image including the ratio set had a total of p^2 channels, where p is the number of original channels. For each of

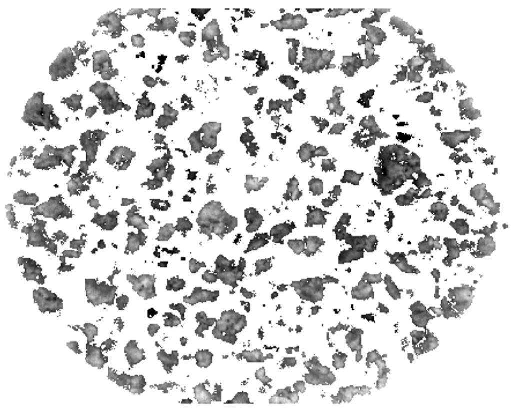

Figure 2. 850 nanometers: processed image: only local maxima remain.

the channels in this new image, a mask was created to include only the local maxima of the meat granules using a mathematical morphological operation, called the h-domes technique.[2] The very coarse surface of the minced meat gives rise to shadows with less information, which is why only the fully illuminated areas of the images are considered in the analysis, as seen in Figure 2.

The preprocessed p^2 channels were then converted to intensity densities, where the 1st, 5th, 10th, 25th, 50th, 75th, 90th, 95th and 99th percentiles were calculated. The percentiles give information about the shape of each of the p^2 density estimations, and are used as covariates in a now very ill posed linear regression problem of the form

$$y = Ax + b + \varepsilon$$

The actual water content from is used as the dependent variable y, and the expanded feature space of the multispectral images is used as the independent variable space x.

A large amount of the calculated variables are nearly linearly dependent, and bring no actual information. This means a standard PLS calibration would give us a very large and complex model. In order to get a more parsimonious and interpretive model, a sparse method is utilised to select relevant features. Many sparse methods exist to solve such problems, where a very well known and intuitive method is the stepwise selection method, chosen to solve this problem.

Results and discussion

The very sparse set of NIR measurements made this an interesting study. Even though the water absorption band at 850 and 970 nanometers are relatively weak compared to bands at lower frequencies we managed to get good correlation results with independent chemical measure-

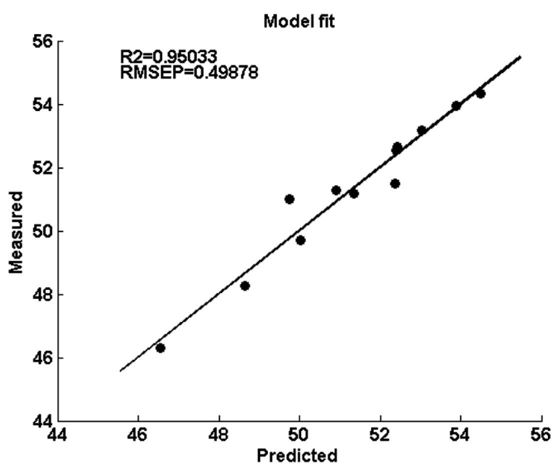

Figure 3. The resulting model shows good correlation between measured and predicted values of water.

ments. A value of R^2 of 0.95 was obtained between the predictions and the measured response in is seen in Figure 3.

The final model selected by the stepwise regression was

$$y = \alpha_1 q(\lambda_{970}, 50\%) + \alpha_2 q(\lambda_{890}, 99\%) + \alpha_1 q\left(\frac{\lambda_{920}}{\lambda_{910}}, 1\%\right) + \varepsilon$$

α_i denotes the coefficients, q denotes the quantile function with two parameters, the first being the variable from the expanded basis, and the second being the quantile-number. In this study, the absorption bands at 970 and 890 nanometers play the most important role in the prediction model, which had a p-value of 0.03. The model performance was calculated using a Leave One Out Cross Validation (LOOCV) scheme, due to the small amount of observations.

Due to water bands high sensitivity to temperature, it is of course important to emphasise that the measurements in this experiment were performed at 20°C. This means that for on-line use, a calibration needs to be performed in order to compensate for the temperature.

References

1. S.B. Daugaard, J. Adler-Nissen, J.M. Carstensen *Food Control* **21(5),** 626 (2009).
2. Luc Vincent. In *IEEE Transactions on image processing*, **2(2),** 1993.