Visualisation of water distribution in bread by near infrared imaging

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Introduction

Objective and goal

Bread is probably one of the oldest prepared food types, dating back to the Neolithic era. Bread is prepared by baking or cooking a dough based on flour, water, yeast, salt, sugar, and other ingredients like. Fresh bread is valued for its taste, aroma, and texture. Bread that has stiffened or dried past its prime is said to be stale.

Ensuring and keeping bread fresh is important for both consumers and bread manufacturers. Preventing the bread from drying out and maintaining a uniform water distribution is important for bread to be perceived as being fresh. The bread composition, production process and storage conditions all play an important role in keeping bread fresh.

Traditional single point NIR techniques are commonly used to determine a variety of food properties. Sørensen[1] successfully used NIR to analyse bread, and predicted the content of protein, fat, dietary fibre, sugar, ash, saturated fatty acids, mono-unsaturated fatty acids, poly-unsaturated fatty acids and Na. There are numerous aspects of food and ingredient properties that result from heterogeneity in composition. Understanding and monitoring food ingredients, as well as final food properties, is of considerable importance for quality assurance within the food industry. If food ingredients are of an unacceptable quality or if contaminants are by accident added to the food, they could result in unforeseen consequences. Enormous amounts of food, already delivered to the distributor would be rejected, not to mention the bad reputation that the manufacturer would get with this type of accident. This is a consequence that the manufacturer cannot afford.

Hyperspectral NIR imaging is a state-of-the-art technique, as it has the potential to determine the spectral as well as the spatial information in the sample. By monitoring characteristic spectral features or by applying a calibration model to a spectral image, it is possible to generate a prediction image, visualising a specific spatial distribution e.g. the moisture distribution in bread.[2] In addition to the amount of information that can be extracted from the hyperspectral image, some other benefits compared to traditional single point NIR spectroscopy, should be mentioned. The hyperspectral imaging technique requires significantly less sample preparation and is likely to detect small material and chemical changes, which are a result of the spatial information plus non-invasive sample preparation.

The objective of this study was to investigate the possibility of developing a NIR imaging calibration model, suitable for monitoring the water distribution in different types of bread. A robust method would be of great importance for the research and development of commercially produced breads.

Materials and Methods

Sample preparation

Three types of bread were used in this study, two toasts (Toast 1 and Toast 2) and one free-standing bread (Kohberg trianon hvedetoast, toast made at Danisco and Schulstad Bondebrod). For each bread type, 3 or 4 replicates (loaves) were used in the study. Samples were collected over a period of 11 days including days 1, 4, 7 and 11, after the bread was baked. The sampling started on day one with slices collected from the middle of the loaf. Each slice was analysed with the spectral camera and then for the calibration model, the center and a near crust piece were cut from the bread. The cuts were analysed with the spectral camera, and water content determined by weight and oven drying, for 3 hours at 105°C. The water content was calculated as percentage of the total wet weight. In total 151 bread slices were measured over 11 days.

Hyperspectral imaging

The SisuChema workstation (Specim Imaging Ltd AB, Oulu, Finland) ranging from 1000-2500 nm, was used for NIR imaging measurements. Each measurement was performed using 1.7 ms exposure time, 31 mm lens and 100 mm field of view.

Data pre-treatment

Each NIR image (sample) is comprised of a three-dimensional data matrix, where each pixel is one spectrum. This matrix is referred to as $\mathbf{X}_{3D}$. The background exclusion was performed in the software Evince Image 2.3.9 (UmBio AB, Umeå, Sweden) using PCA to separate bread signals from background noise. The noise exclusion is done per sample, using no scaling or centering of the data. According to the background noise exclusion, the $\mathbf{X}_{3D}$ data were averaged in Matlab, creating a vector for each sample. All samples were put into one matrix, $\mathbf{X}$[N,K].

Table 1. Water variation of the different bread types and for the combined dataset, *n* = number of bread slices.

	N	Min	Max	Mean	*STDEV*
Free standing bread	64	41.8	48.1	45.0	1.7
Toast 1	46	35.3	44.4	39.5	2.6
Toast 2	41	37.8	48.9	43.5	3.9
All breads	151	35.3	48.9	42.9	3.6

Table 2. Model overview. Four models shown, three bread types and one global model combining data from the three bread types. Number of samples in models (n), number of loaves in test set (test set), number of slices in test set (test sets size), number of principal components in the model (PLS terms), average cross-validate explained variance (total Q2Y) and average root mean squared error of prediction (*RMSEP*).

	N	Test sets	Test set size	PLS terms	Total Q2Y	*RMSEP*
Free standing bread	48	4	16	4	0.82	0.72
Toast 1	30–31	3	15–16	4	0.86	0.87
Toast 2	25–29	3	12–16	4	0.98	0.69
All breads	104–107	3	44–47	4	0.94	0.87

Models

The **X**[N,K] data was evaluated for outliers by using PCA for each type of bread. Prior to PLS regression, the data matrix, **X**[N,K], was transformed and scaled using SNV (row-wise) and

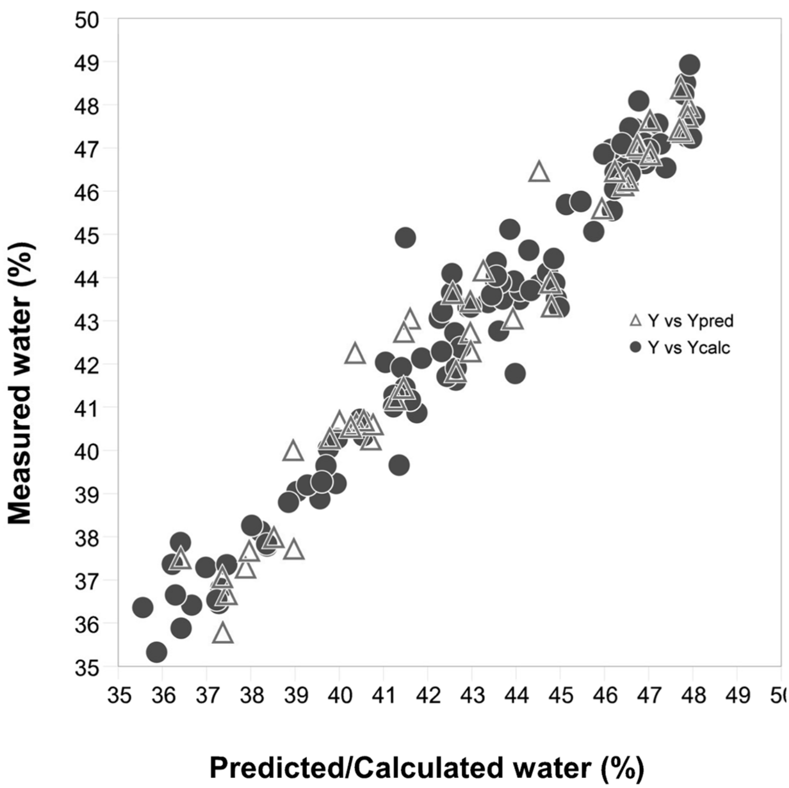

Figure 1. All 3 bread types used for modelling water content. Measured water content (%) vs. model calculated and predicted from test set.

centering (column-wise)[3–5]. PLS Models were built in the software Evince Image between the **X**[N,K] matrix and the moisture vector Y.

Results and discussion

Calibration development

Calibration by PLS regression was performed using center and near-crust cuts from the three bread types. A global model was developed combining data from all three bread types. The number of bread slices analysed and water variation of the sample sets are listed in table 1.

Individual models were made, one for each bread type and one global model containing all of the breads. Several calibration models were made for each bread type (one for each loaf). In each of these models one loaf (in turn) was excluded from the data and used as an external test set. For the global model one loaf of each bread type was used as a test set. Model validation was performed by calculating the root mean square error of predictions, RMSEP, for each model using

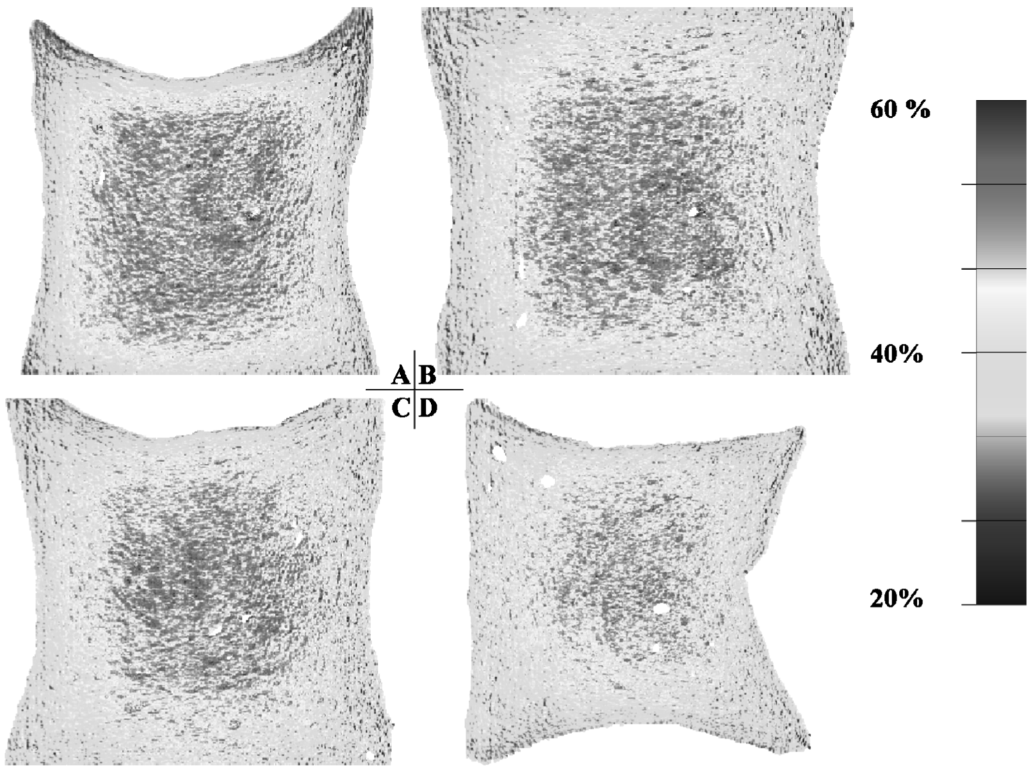

Figure 2. Predictions of water content and distribution in four slices of toast (Toast 2) as a function of storage time, day 1 (A), day 4 (B), day 7 (C) and day 11 (D).

the external test set[5]. Table 2 summarises the different models developed. Figure 1 shows the measured water content versus the calculated and test set predicted water content.

Spatial distribution of water in bread

By using the calibration model, water could be predicted in each pixel in the spectral image, thereby showing the spatial distribution of water in bread. Figure 2 shows how the global All bread model has been used to predict water in Toast bread.

The four different images in Figure 2 represent different ages of the toast bread (1, 4, 7 and 11 days). It is noticeable that fresh toast has both the lowest and highest water concentrations at the crust and centre of the slice. The water becomes more homogeneously distributed as the bread is stored.

Conclusion

This study demonstrated that it is possible to use hyperspectral NIR images to predict the water content in bread without any sample preparation, i.e. on whole slices of bread. The study also demonstrates that calculation of a calibration model can be used to visualise the spatial distribution of water in bread. This type of hyperspectral imaging application can easily be used in routine analysis in research and development of bread. The method can easily be extended to other ingredients in bread and thus become an even more valuable tool in bread research.

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