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Prediction of sensory texture quality attributes of cooked potatoes by NMR-imaging (MRI) of raw potatoes in combination with different image analysis methods

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Abstract

Nuclear magnetic resonance imaging (NMR-imaging), the so-called magnetic resonance imaging (MR-imaging), was performed on five potato varieties stored at 4 °C and 95% relative humidity for two and eight months, respectively. An image analysis on the obtained data and subsequent sensory analysis of the cooked potatoes displayed the high potential of employing advanced image analysis on MR-imaging data from raw potatoes to predict sensory attributes related to the texture of cooked potatoes. In contrast MR-imaging data were not found to correlate with specific gravity of the potatoes even though this parameter is normally found to correlate with the sensory texture quality of cooked potatoes. We suggest that this imply that MR-imaging beside giving well-known information about water distribution also gives information about anatomic structures within raw potatoes, which are of importance for the perceived textural properties of the cooked potatoes.

Keywords: NMR-images; MRI; Image analysis; Feature extraction; Potato texture; Quality prediction; Magnetic resonance imaging

1. Introduction

Texture is a very important quality attribute in most food products. For most food products a high biological variation between replicates exists. This biological variation is one of the main challenges for the industry, as the increased purchasing power and the increased awareness of food quality by the consumers result in a demand for products of high and uniform quality. Hereby it becomes very important for the industry to be able to supply products of uniform quality. Consequently, the industry needs rapid on-line and at-line methods to (1) sort the raw material into given texture categories prior to processing, (2) predict the optimal use of the raw material and (3) adjust the processing to obtain the optimal quality of the processed product.

Due to their nature, non-destructive measurement methods are very attractive in the development of on-/at-line methods. While infrared spectroscopic methods have become very popular for this purpose in the food industry, it is not until recently that nuclear magnetic resonance (NMR) have been accepted as a technique with relevance for quality determination. Low-field 1H-NMR relaxation or high-field NMR-imaging, the so-called magnetic resonance imaging (MR-imaging or MRI) have shown to have potential to predict food quality attributes, and hereby may be attractive methods to implement as in-/at-line methods in the future food production.

NMR relaxation is a rapid non-invasive method to determine the distribution of water in foods (Cornillon, 1998; McCarthy, 1994). Water distributions in foods are very important characteristics in relation to food texture

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quality. Low-field NMR relaxation data have thus been shown to be highly correlated with the texture properties in rice, bread, meat and potatoes (Fjelkner-Modig & Tornberg, 1986; Ilker & Szczesniak, 1990; Ruan et al., 1997; Seow & Teo, 1996; Steen & Lambelet, 1997; Thybo, Bechmann, Martens, & Engelsen, 2000).

Like NMR relaxation, MR-imaging is also able to measure water properties, e.g. the abundance and the spatial distribution of free and bound water inside biological materials (McCarthy, 1994). In contrast to commercial low-field relaxation equipment, existing MR-imaging apparatus can already be used as non-invasive measuring methods on most foods. In the past, MR-imaging has mostly been applied within the medical area, where it has achieved general acceptance as a powerful tool for the diagnosis and assessment of tumours in the human brain and liver by visual interpretation of images (Lerski et al., 1999). As the technology has matured, new applications have been developed directed at non-medical areas, such as physiology and anatomy (MacFall & Van As, 1996). MR-imaging techniques have been used for determination of the internal structure and the quality of fresh and processed products mostly in terms of internal breakdown, bruises, voids, and post-harvest studies of fruits and vegetables (Clark, Hockings, Joyce, & Mazucco, 1997; McCarthy et al., 1995). For apples this non-destructive method has been used to investigate internal changes in watercores and development of browning during storage (Clark & Burmeister, 1999; Clark & Richardson, 1999).

MacFall and Van As (1996) were the first to show that different MR-imaging methods of potatoes result in different patterns of contrast and information. A subsequent study demonstrated the use of MR-imaging in displaying the water distribution in potatoes during a drying and a water re-absorption process (Ruan et al., 1997). In most of the investigations, the MR-images were analysed quantitatively in terms of relaxation times (T_1 and T_2) or qualitatively by e.g. ocular judgement of the MR-images. In contrast, the use of image analysis on MR-images is sparsely described in the food literature.

Image analysis is based on a resolution of the structure in the image, the so-called texture of the image (Haralick, Shanmugam, & Dinstein, 1973; Materka & Strzelecki, 1998). There is no generally accepted definition of image texture. However, image texture may be viewed as a regular pattern that fills fragments of image surface. Such fragments have two main properties: there is significant variation in intensity levels between nearby pixels, and there is homogeneity at some spatial scale larger than the resolution of the image. Intuitively, texture provides a measure of properties such as lightness, granulation, uniformity, density, roughness, regularity, linearity, frequency, phase, directivity, coarseness, randomness, fineness, smoothness, etc. In computer image analysis, there are a number of techniques for calculation of image texture properties (features). These are usually categorised into *structural*, *statistical* (stochastic), *model-based*, and *transform* methods (Haralick, 1979; Materka & Strzelecki, 1998). It can be difficult to predict which of these methods and which features computed by these methods are the most useful for classification purposes of examined image textures.

Digital images of biological origin usually have heterogeneous composition. Within such images there may be fragments representing several, separable parts of the studied object as well as of the background surrounding this object. Often, the object itself or an interesting part of the object occupies only a small portion of the image domain. In such a case, the region of interest (ROI), which holds information about aspects of interest of the studied object, must be created. However, it must be small enough to exclude other irrelevant image regions. For these reasons, there is a need to carry out research in order to optimise the practical use of image analysis on both (I) finding/defining an assortment of features that would extract information useful for classification of different biological images and (II) finding regions of interest within such images that would be the most appropriate for computing these features.

Recently, Balzarini, Nicula, Mattiello, and Aliverti (2001) carried out quantification and description of fracture network in lithologies by image analysis of MR-images. Computer-assisted image analysis has previously been used to determine the information on texture/structure in the images object composed of different plastic foams and glass beads producing different porosity (Materka, Strzelecki, Lerski, & Schad, 1999a, 1999b, 2000). These studies showed that it is possible to classify objects with different internal structure with respect to MR-image grey tone distribution of the images (white to black). However, this method has until now only been used in structure classification of different tumours in the human brain and liver (Lerski et al., 1999), and only very recently has it been used for simple analysis of the structure and texture in potatoes (Thybo, Andersen, Karlsson, Dønstrup, & Stødkilde-Jørgensen, 2003). The latter study showed that in order to extract more relevant quantitative information from the images, more advanced image analysis of MR-images seems necessary. Therefore the new image analysis computer package for extraction of numerous different image texture features in digitised images (Materka et al., 1999a, 1999b, 2000) may be useful in future interpretation of MR-imaging data on foods.

The sensory texture quality is of the uppermost importance in cooked potatoes, as this is one of the most critical quality attributes in consumer evaluation of potatoes. The biological variation between potato tubers is high and is known to influence the texture of cooked potatoes. Consequently, development of on-line/at-line sensors enabling a grading and sorting of potatoes in relation to their final qualities before marketing, long-term storage or processing is highly relevant. As mentioned above it was recently shown that MR-imaging is able to illustrate an uneven spatial distribution of water within potato tubers indicating a high variation in the distribution of water and an abundance of water between tubers (MacFall & Van As, 1996; Thybo et al., 2003). In the latter study, the relationship between simple histogram features from the image analysis of the MR-images and dry matter content of potatoes was also investigated, however, no high correlation was obtained.

The aim of the study was to investigate the ability of using the non-destructive and non-invasive MR-imaging technique to describe the sensory texture quality of cooked potatoes. This was determined by studying the correlation between advanced image analysis features determined in different regions of raw potatoes, and sensory texture attributes of cooked potatoes. Moreover, correlations between specific image features and sensory data were also carried out.

2. Material and methods

2.1. Potatoes

Five potato varieties (Sava, Berber, Ditta, Bintje-medio-dry-matter and Bintje-high-dry-matter) grown in experimental fields at the Danish Institute of Agricultural Sciences were investigated. Potato samples were harvested in 1999 and analysed after two and eight months of storage in November 1999 and in May 2000, respectively. The potatoes were stored at 4 °C at 95% relative humidity. To obtain a homogeneous material within a given sample, the five potato varieties were graded in three dry matter bins with 1% span in dry matter using a salt solution. This selection procedure gave a total of 27 different potato sample sets, as Bintje-high-dry-matter was not present in the second storage time.

Five potato tubers were randomly selected for specific gravity analysis and MR-image analysis. Forty potato tubers were used for sensory analysis.

2.2. Specific gravity

Specific gravity was determined as the ratio: Weight in air/(weight in air−weight in water) (Schippers, 1976).

2.3. MR-image acquisition

Five potato tuber replicates of each sample were scanned by MR-image equipment (Sisco 300/183,Varian Inc. Palo Alto Ca., USA) by scanning a 2 mm thick layer in the middle of the tuber. The images were acquired as T_1 weighted spin echo images with a repetition time $T_R = 600$ ms and echo time $T_E = 10$ ms, and a field of view of 6 cm. Each image was obtained as a sum of 2 scans with a resolution of 256×220 points in the time domain, which was interpolated to 256×256 points during Fourier reconstruction. Each image was then converted to the standard BMP image format and represented by 256 grey levels. Unfortunately, for technical reasons a gain setting of the scanner could not be reproduced between the two storage times. To minimise this error, the two sets of images were re-normalised to have the same average background level.

2.4. MR-image feature extraction

Textural features of potato interior in MR-images were computed using the MaZda software version 2.21 (Szczypiński, Materka, & Strzelecki, 2001). The software calculated 259 various image texture features for grey-level images, derived from first-order histogram, image gradient map, co-occurrence matrix, run-length matrix and parameters of autoregressive model. MaZda also computed feature maps that represented distributions of given features within image.

The first-order histogram shows the distribution of the image pixels' grey-level intensity. Using this method, nine features were calculated. Calculation of the grey-level histogram involved single pixels thus it simply summarises some statistical image information without gaining any information about the image texture. Generally, histogram-based features provide information about average level of intensity, variation of intensity, symmetry and flatness of histogram.

Image gradient calculation is one of several commonly used techniques for finding edges within image. Hence, five gradient-based features provided quantitative information about borders between light and dark image elements.

Run-length matrix (RLM) is defined as the number of times that a run has a certain grey level. Five run-length matrix-based features were computed for four directions of run (horizontal, vertical, 45° and 135° run).

Co-occurrence matrix (COM), the second-order histogram, is a square matrix that estimates joint probability of two pixels having particular intensities. Eleven features (Haralick et al., 1973) were computed for four directions and five distances between pixel pairs—in total 220 features.

RLM based features and co-occurrence matrix-based features give quantitative information about structure of image texture pattern (Materka, Strzelecki, & Szczypiński, 2000). These are sensitive to the directivity of texture. Comparison of features computed for different directions provided important knowledge about texture directivity. Twenty RLM features were calculated.

The autoregressive model (ARM) assumes that pixel intensity is a weighted sum of neighbouring pixel intensities. Four parameters were computed for minimal noise variance. The ARM parameters describe relations of grey-level intensities between neighbouring pixels.

Due to the radial directive structure in a potato (Fig. 1a–c) determining a horizontal (Fig. 1d) and a vertical (Fig. 1e) structure, the image analysis was performed on these regions and on the full region. Feature maps were computed for these three regions. Features derived from COM, RLM and ARM are sensitive to the texture directivity. Due to this, the values computed within regions containing texture with vertical directivity differ from the values computed within regions containing horizontal directivity texture. When striking an average of the horizontal and vertical directivity, some important information may be lost. The feature maps (Fig. 1d and e) demonstrate two main regions with low and high brightness representing low and high feature values.

2.5. Sensory analysis

Whole potatoes of each sample were peeled and boiled in water for 20–25 min, depending on variety. All samples were analysed in four replications in a randomised design with six samples per sensory session. The samples were evaluated while hot, and one tuber per sample was served for each assessor. A panel of ten trained assessors evaluated the texture by quantitative descriptive analysis (Thybo & Martens, 1998). The sensory texture attributes included: hardness, cohesiveness, adhesiveness, mealiness, graininess and moistness. The attributes were evaluated on a 1–15 point unstructured line scale with the anchor point 'none' on the left side and 'very strong' on the right side. The mean of the assessors' scores was calculated and used for statistical analysis.

2.6. Statistical analysis

The variations in sensory texture attributes and MR-image features were determined by multivariate data analysis on mean data of the replicates using The Unscrambler statistical package (v7.5 CAMO A/S, Norway, www.camo.com). Principal component analysis (PCA) revealed the structure in the data. Partial least squares regression (PLSR) was used to investigate relationships between sensory attributes and MR-image features in terms of prediction of the sensory texture attributes (Y-variables) from MR-image features (X-variables) on the data set of 27 samples. Different groups of image features (X-variables) were included in the prediction. MR-image features from (1) the vertical region, (2) the horizontal region or (3) the full region were investigated by the following features (A) histogram, (B) gradient, (C) RLM, (D) COM and (E) ARM.

The prediction of specific gravity (Y-variable) from MR-image features (X-variables) was investigated by

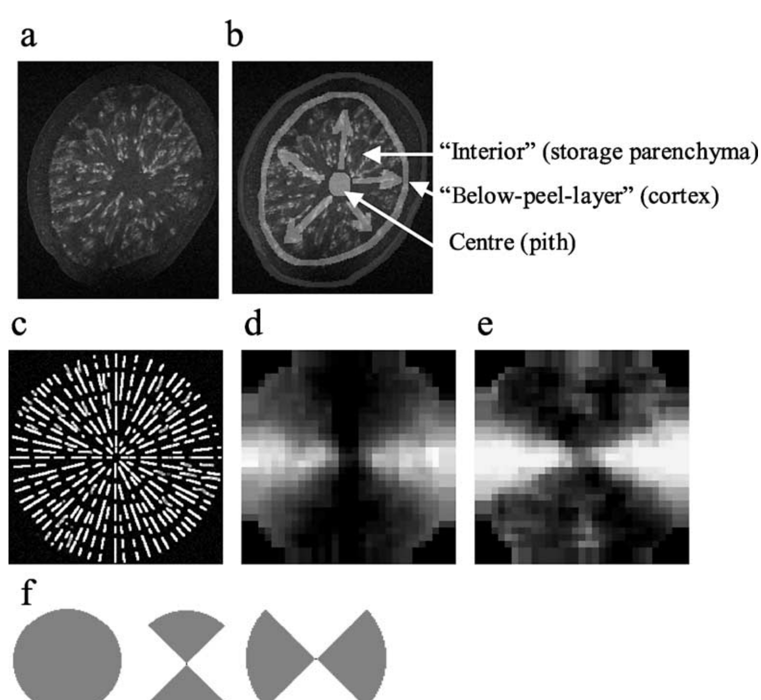

Fig. 1. MR-image of a raw potato. (a) indication of radial structure, (b) artificial model of the radial structure, (c) feature maps computed by MaZda software showing different values for horizontal and vertical structure (d, e) and different templates of regions (full, vertical and horizontal) for image analysis (f).

PLSR. Since specific gravity and MR-images were obtained on the exact same potato tuber due to the non-destructive character of the methods, this data set included 135 objects (27 samples * 5 replicates). The used image analysis approach determines many different MR-image features. Therefore an analysis of how the specific features correlated with the obtained sensory attributes and specific gravity was also included, as this will be a natural step to increase effectiveness and optimise future image analysis of MR-images. From the PLSR model, the significant features were extracted by the so-called Jack-knifing (Martens & Martens, 2001). The significant MR-image features were determined by a double Jack-knifing where the data set was separated into five subsets of samples. In each sample subset, the predictive performance of the significant features was investigated. The significant features were defined as those being significant in at least two of the five sample subsets.

For all predictions, the performance of the prediction was determined as the explained variance of the Y-variables by the X-variables, correlation coefficients between measured and predicted variables and root mean-squared error of prediction (Martens & Martens, 2001). All the data were standardised, and the model evaluations were based on full leave-one-object-out cross validation (Martens & Martens, 1986).

3. Results and discussion

3.1. Regions of interest within potato for image analysis

Fig. 1a illustrates a typical structure in a MR-image from a potato. Three different areas were distinguished: a centre (pith), "below-peel-layer" (cortex), and the area in between called "interior" (storage parenchyma) (Fig. 1b). The grey level distribution within the centre and the below-peel-layer was rather constant. In contrast, a large structure variation was visible in the interior part of the potato. Due to the anisotropy of the potato tissue, the structure in the image was basically the same independently of how the potatoes were placed in the MR equipment. A visual inspection of the image indicated that an artificial model of the structure could be described by radial lines starting from the centre of the potato moving to the outer layer (Fig. 1c). The feature maps from the image analysis (Fig. 1d and e) demonstrated two main regions, a vertical region and a horizontal region with low and high brightness representing low and high feature values. Due to this, the image features computed within regions containing texture with vertical directivity differ from those computed within regions containing horizontal directivity texture, and maybe thus contributing to different types of information in the images. Consequently, image features were calculated from both the vertical and the horizontal region and compared with image features from the full region to optimise the regions of interest within a potato image.

3.2. Classification of potato varieties by MR-image and sensory analyses

Fig. 2 illustrates the variation in the 259 MR-image features obtained from the full region within the potato using PCA. Three principal components (PCs) accounted for 80%, 8% and 5% of the total variation in the MR-image features and summarised the variations between varieties, storage times and dry matter grading (Fig. 2a). The differences between the varieties caused the largest variation in the MR-image features (PC1) (Fig. 2b). A minor effect of storage was observed in PC2. The effect of dry matter grading was limited. The MR-images showed differences in colour intensity and structure between varieties, and thus differences in water distribution and restraint. The darker the tissue, the more free is the present water. This shows that water is unevenly spatially distributed within the potato tubers and with different abundance. The patterns in the images of the potatoes showing that the darkest sections was found in the centre of the potato tuber and in the layer below peel are similar to the patterns reported by others (MacFall & Van As, 1996; Thybo et al., 2003). A PCA on the MR-image features from the horizontal and the vertical regions resulted in the same classification of variety, storage and dry matter as was found when the full region was used.

Likewise, a PCA of the sensory data showed a similar grouping of the potato samples with respect to variety, storage and dry matter variation (Fig. 3). This indicates that the sensory data and the MR-image features described a similar variation. 'Bintje-medio-dry-matter' was a very mealy and adhesive variety with low cohesiveness and hardness. Oppositely, the varieties Sava and Ditta were low in mealiness and adhesiveness and score high on cohesiveness and hardness. The variety Bintje-high-dry-matter was mealy with a grainy texture. For all varieties, moistness was higher after eight months of storage compared with two months of storage (Fig. 3, PC 2). The sensory attributes spanned out the variation in texture quality, however, even in a third PC cohesiveness and hardness were highly correlated, and these variables expressed the same information. Consequently, cohesiveness was removed in the subsequent prediction of texture qualities.

3.3. Prediction of sensory texture quality from MR-images

The MR-image features extracted from the three regions (full, horizontal and vertical) within the potato predicted the sensory attributes to different extents

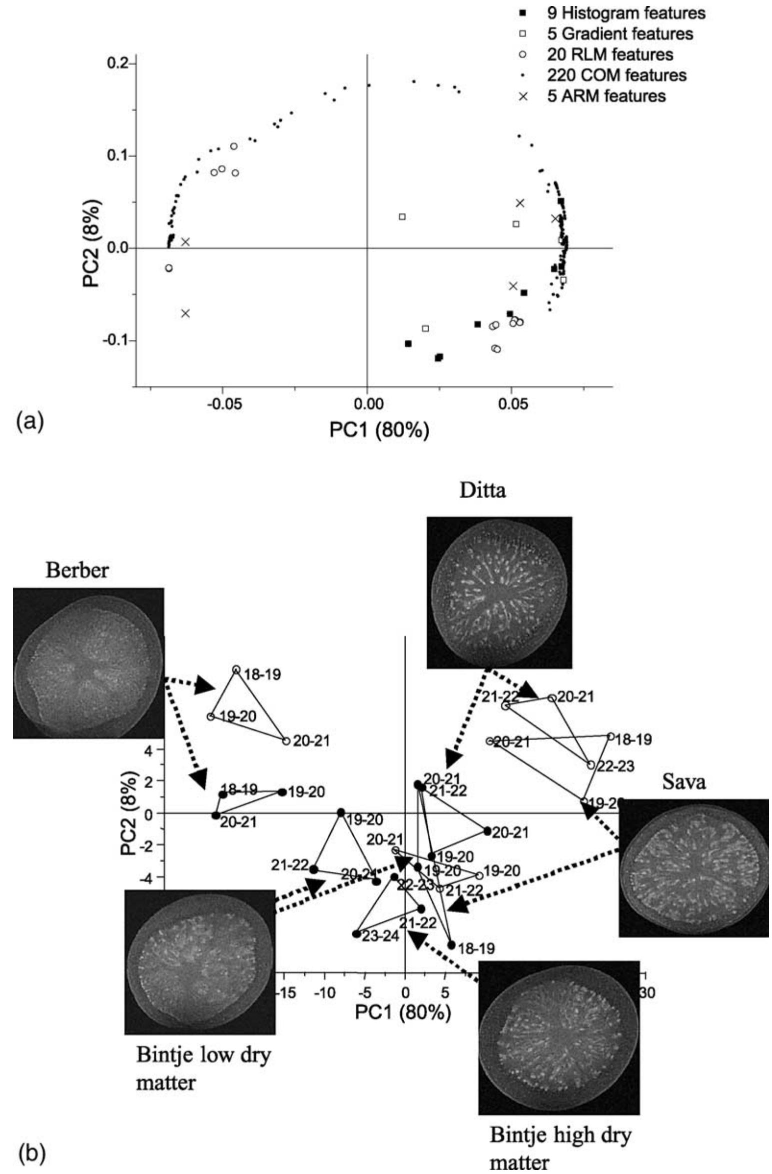

Fig. 2. A PCA plot of the variation in 259 MR-image features (a, loading plot) obtained in the full region in 27 potato samples (b, scores plot). Footnote: the numbers represent percent dry matter range. (●) November 1999 storage, (○) May 2000 storage.

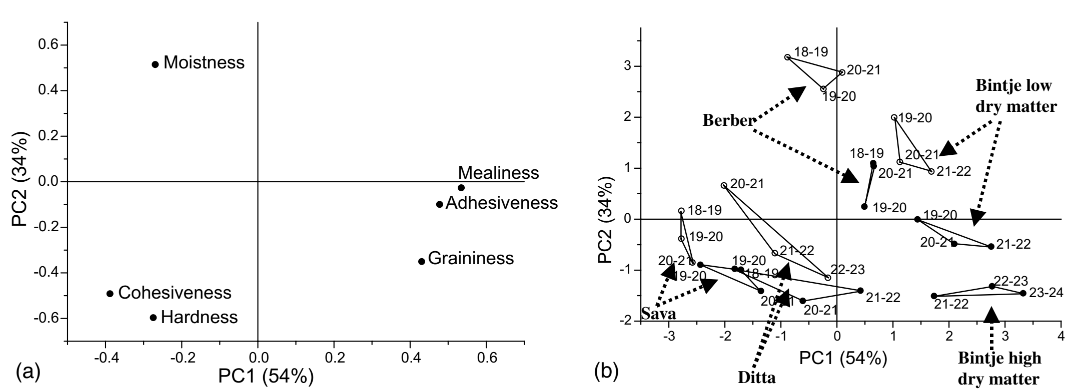

Fig. 3. A PCA plot of the variation in 6 sensory attributes (a, loading plot) in 27 potato samples (b, scores plot). Footnote: the numbers represent percent dry matter range. (●) November 1999 storage, (○) May 2000 storage.

(Table 1). The explained variance, correlation coefficients (Table 1) and RMSEP values indicated that the highest prediction was obtained by the MR-image features from the full region within the potato compared with the MR-image features from horizontal and vertical regions. For hardness, 76% of the variation was predicted by all the MR-image features, for adhesiveness 54% and for moistness 50% of the variance was predicted, resulting in correlation coefficients of 0.86, 0.72 and 0.69, respectively. For the attributes mealiness and graininess, the predictions were rather low as the explained variances were below 55%. This means that the geometrical attributes giving the mealy and granular perception were not correlated with MR-image attributes. As the full region described the largest proportion of the variation in the sensory attributes, only the full region was subsequently used in the prediction of the individual sensory texture attributes from the individual groups of MR-image features. Interestingly the vertical region seemed to predict mealiness considerably better (46%) than both the full and the horizontal regions, and this implies that a further emphasis on regions of interest may also make prediction of mealiness possible by MR-imaging.

3.4. Individual image features for prediction of texture quality

To further reveal the information obtained by the image analysis on the potato MR-images, a correlation analysis between the specific image analysis features and the sensory attributes hardness, adhesiveness and moistness having high correlation with all 259 MR-image features was carried out. Furthermore, a reduction of extracted features was exploited. An overview of the predictions of hardness, adhesiveness and moistness from the individual groups of MR-image features is given by correlation coefficients between measured and predicted sensory attributes in Table 2. A PLS1 regression was performed for each sensory attribute and feature group in turns. The COM features explained the highest proportion of the variation in hardness (78%). The COM features could almost explain the same amount of variation in hardness as the variation explained by all five feature groups. However, the histogram features and the gradient features explained some part of the variation in hardness (63% and 59%, however). Groups of sub-features within the COM features were highly correlated with hardness. These features were also highly interrelated. Therefore non-correlating features were extracted, and the prediction of hardness from 3 features gave a correlation between measured and predicted hardness of $r = 0.880$ (Fig. 4). In comparison, the inclusion of all 220 COM features gave a correlation of $r = 0.876$ (Table 2) indicating that a variable selection can be performed without loss in prediction of hardness.

For adhesiveness, the RLM features and the COM features explained the highest proportion of the variation (64% and 57%, respectively). Twenty features were included in the RLM features. Three groups of RLM features contributed to the explanation of adhesiveness.

Table 1
Prediction of five sensory texture attributes from the full set of 259 MR-image analysis features (Histogram, Gradient, RLM, COM, ARM features) determined in three regions within the potatoes (see Fig. 1)

Predictor	259 features from the full region		259 features from the horizontal region		259 features from the vertical region	
Sensory attribute	% explained variance (PCs)	*r*	% explained variance (PCs)	*r*	% explained variance (PCs)	*r*
Hardness	**76 (4)**	**0.862**	70 (4)	0.824	70 (4)	0.830
Adhesiveness	**54 (4)**	**0.720**	45 (4)	0.658	52 (4)	0.710
Mealiness	36 (4)	0.584	24 (4)	0.480	46 (4)	0.660
Graininess	29 (4)	0.526	26 (4)	0.491	34 (4)	0.570
Moistness	**50 (4)**	**0.690**	37 (4)	0.582	47 (4)	0.671

The predictions are given by correlation coefficients between measured and predicted sensory texture attributes using PLS regression.

Table 2
Prediction of three sensory texture attributes and specific gravity from the Histogram, Gradient, RLM, COM and ARM feature groups from MR-image analysis given by correlation coefficients between measured and predicted sensory texture attribute using PLS regression

Predictor	Histogram features	Gradient features	RLM features	COM features	ARM features
Attribute	*r*	*r*	*r*	*r*	*r*
Hardness	**0.791**	**0.751**	0.250	**0.876**	0.677
Adhesiveness	**0.671**	0.434	**0.760**	**0.734**	0.622
Moistness	0.485	0.438	0.555	**0.689**	0.430
Specific gravity	0.456	0.367	0.398	0.336	0.314

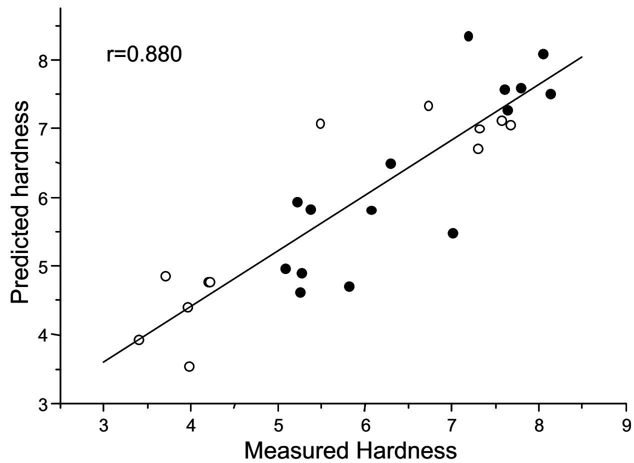

Fig. 4. A PLS prediction of sensory hardness from three MR-image features (COM features). Footnote: (●) November 1999 storage, (○) May 2000 storage.

A selection of one variable from each of these groups gave a correlation coefficient between predicted and measured adhesiveness of $r = 0.784$ (Fig. 5) compared with $r = 0.760$ for all twenty RLM features and $r = 0.734$ using all COM features (Table 2).

The highest predictions of moistness were obtained by using the COM features ($r = 0.689$, Table 2). Thus, the prediction of moistness was lower than the prediction of hardness and adhesiveness. A specific group of COM features were highly correlated with moistness. However, these features alone could not predict moistness. A set of three COM sub-features predicted moistness ($r = 0.694$) to the same value as was found by using all COM features.

The present research on analysing the structures in the MR-images contributes with knowledge of high importance in relation to rational development of potential on-line methods to determine sensory texture quality. The COM features were very relevant features for the prediction of hardness, adhesiveness and moistness, however, it was not the same sub-groups of COM features that predicted hardness, adhesiveness and moistness (not shown). This means that the COM sub-features determined different structures with varying relevance for hardness, adhesiveness and moistness. Moreover, the RLM features predicted a larger proportion of the variance in adhesiveness. Once more, this indicated that different MR-image structures were relevant for the individual sensory texture attributes, and these structures could be identified and quantified.

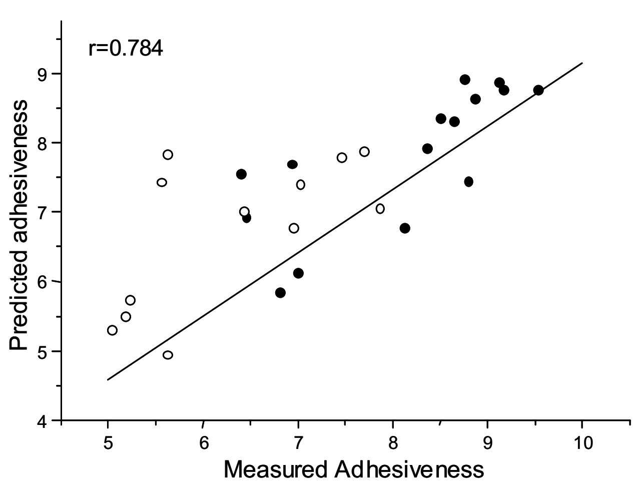

Fig. 5. A PLS prediction of sensory adhesiveness from three MR-image features (RLM features). Footnote: (●) November 1999 storage, (○) May 2000 storage.

The MR-image features predicted 70% of the variation in hardness, which means that MR-imaging may be a useful method to sort potatoes with regard to hardness in the cooked potato. Hardness as well as mealiness, adhesiveness and moistness is an important quality attribute for sorting potato tubers into classes with various technological qualities. Therefore these sensory attributes are relevant for the usage of potatoes in the industry, and these results may thus contribute to the development of on-line methods to determine final quality and usage of potatoes from measurements on raw potatoes.

3.5. Prediction of specific gravity from MR-images

The specific gravity of the 135 objects (27 samples × 5 replicates) was normally distributed within the range 1.056–1.095 g/cm^3. This range in specific gravity corresponded to a dry matter variation of approximately 14–23% dry matter. The 259 MR-image features obtained using the full region approach showed no high correlations with specific gravity ($r = 0.461$, Table 2). The prediction of specific gravity from each of the five MR-image feature groups ranged from $r = 0.336$–0.461 with the highest prediction for the histogram features and all 259 features. The low correlation between the MR-image features and specific gravity indicates that MR-imaging does not reflect specific gravity, which is highly correlated with the dry matter content of the potatoes. A poor correlation between dry matter and the histogram features from MR-images has previously been reported (Thybo et al., 2003). These results strongly indicate that MR-images determine structural/anatomic features within the raw potato which are of importance for the sensory texture experience of cooked potatoes and different from those related to dry matter of the raw potato. NMR relaxation data from raw potatoes have been shown to be highly correlated with the dry matter content (Thygesen, Thybo, & Engelsen, 2001) which also explains some of the sensory texture attributes in cooked potatoes (Thybo et al., 2000). Overall, this indicates that the use of MR-imaging data from raw potatoes including both image analysis data as used in the present study and more traditional relaxation characteristics from the images would be a highly relevant approach in the prediction of sensory texture quality of cooked potatoes. This approach will be reported elsewhere.

4. Conclusions

As one of the first, the present study deals with a quantitative description of MR-images and the correlation with sensory texture quality attributes of a food item. The study clearly shows that features extracted from MR-images of raw potatoes using different image texture analysis methods are able to classify the sensory texture variation in five potato varieties and to predict the sensory texture attributes in the cooked potatoes. Especially the perception of hardness and adhesiveness can be predicted with a high degree of explanation, while moistness can only be predicted to a certain extent. In contrast, neither the sensory attributes of mealiness and graininess nor the specific gravity of the cooked and the raw potatoes could be predicted with the used approach.

Moreover, the present study showed that characteristics obtained by MR-imaging on raw potatoes provide structural/anatomic information of importance for sensory perception of texture in cooked potatoes.

Although the study is of somehow preliminary nature, it displays the high potential of MR-imaging as a future method for quantitative quality evaluation. Finally, the success obtained using image analysis on MR-imaging data from potatoes, as a model food, in relation to a better prediction of food quality seems to guarantee that quality templates for subsequent calibration of the MR-imaging instrument can be developed, thereby enabling a sorting for desired quality attributes.

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