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Prediction of sensory attributes of European Emmental cheese using near-infrared spectroscopy: A feasibility study

R. Karoui [a,*], L. Pillonel [b], E. Schaller [c], J.-O. Bosset [b], J. De Baerdemaeker [a]

[a] *Division of Mechatronics, Biostatistics and Sensors (MeBioS), Department of Biosystems, K.U. Leuven, Kasteelpark Arenberg 30, B-3001, Leuven, Belgium*

[b] *Agroscope Liebefeld-Posieux (ALP), 3003 Berne, Switzerland*

[c] *Büchi Labortechnick, 9230 Flawil, Switzerland*

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Abstract

The present work evaluated the ability of near infrared (NIR) spectroscopy in predicting some sensory attributes of 20 Emmental cheeses originating from different European regions. For the purpose of this study four appearance and texture attributes, namely, adhesivity, friability, elasticity and firmness and six olfacto-gustatory attributes namely, aroma intensity, odour intensity, bitterness, saltiness, acidity and sweetness were selected by the sensory panel. Calibration models between sensory properties and NIR spectra were developed using partial least squares (PLS) regression. The squared correlation coefficients (R^2) were greater than 0.5 for adhesivity, elasticity, firmness, aroma, bitterness, saltiness, acidity and sweetness. In addition, a good correlation between sensory attributes and NIR spectra was found using canonical correlation analysis (CCA). Therefore, this work demonstrates the feasibility of NIR to predict some sensory attributes since a relatively high correlation between sensory data and NIR spectra was found. However, further research with a large data bases will be needed in order to validate the method.

Keywords: Emmental cheese; Near infrared spectroscopy; Sensory attributes; Partial least squares method; Canonical correlation analysis

1. Introduction

Sensory analysis of food involves the measurement, interpretation and understanding of human responses to the properties of food perceived by the senses such as sight, smell, taste, touch and hearing (Martens, 1999; Martens & Martens, 2001). It is important to have a quantitative means for assessing sensory properties in a reasonable way to enable the food industry to rapidly respond to the changing demands of both consumers and the market (De Belie et al., 2003; Martens, 1999). Aroma intensity and flavour are among the most important properties for the consumer and numerous studies have been performed in attempts to find correlations between sensory qualities and objective instrumental measurements.

Cheese is a complex mixture of water, protein, fat, ions, etc. and various chemical compounds that are formed during the ripening process. These latter include carbohydrates, phenolic compounds, organic acids, volatile aroma compounds, residual sugars, etc. all of which can contribute to the sensory characteristics of the cheese.

The quality of cheese can be measured directly by sensory methods or indirectly by chemical, mechanical or optical measurements. For practical reasons, these quality criteria should be easily measurable. Simple and rapid methods are needed for quality control and for screening many samples in a research or development situation. However, many of the above mentioned methods are unsuitable to be used or adopted by the cheese industry for rapid analysis of cheese quality. For example, analysis of volatile compounds in cheese to assess cheese aroma by gas chromatography–mass spectrometry (GC–MS) involves expensive instrumentation and is time consuming.

* Corresponding author. Tel.: +32 (0) 16321470; fax: +32 (0) 16328590. *E-mail address:* Romdhane.Karoui@biw.kuleuven.be (R. Karoui).

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In addition, the current level of knowledge regarding aroma composition of cheeses is such that the prediction of the sensory characteristics of cheese from GC–MS data is only possible for some specific sensory properties. Sensory analysis using trained panel is more effective in assessing cheese quality characteristics; however, this method is also time consuming and expensive. Although the importance of sensory analysis is unquestionable, this method is hardly possible to implement for practical use when many samples need to be analysed on-line or at-line in the food industry (Martens, 1999; Martens & Martens, 2001; Rødbotten, Nilsen, & Hildrum, 2000; Thybo, Bechmann, Martens, & Engelsen, 2000). It would therefore be desirable to replace sensory evaluation by faster, simple, or cheaper instrumental analyses.

Rapid screening techniques to determine quality characteristics of food are of great interest to the food industry (Brøndum, Byrne, Bak, Bertelsen, & Engelsen, 2000; Venel, Mullen, Downey, & Troy, 2001). Spectroscopy in the ultraviolet (UV), visible (VIS) and infrared (IR) regions of the electromagnetic spectrum is becoming a more and more attractive analytical technique for measuring quality parameters in food with decreasing instrument prices and improved equipment and chemometric tools (Brøndum et al., 2000). The main advantages of using spectroscopic techniques are rapid sample data acquisition, the possibility of simultaneous determination of several quality parameters and the ability to replace expensive and time consuming reference techniques (Karoui, Mazerolles, & Dufour, 2003; Thybo et al., 2000).

Among spectroscopic techniques, near infrared (NIR) spectroscopy has been used as a method to predict the quality of different foods and agricultural products due to the speed of analysis, minimal sample preparation and low cost (Osborne, Fearn, & Hindle, 1993). NIR spectroscopy covers the wavelength range from 800 to 2500 nm, but some spectrophotometers allow the inclusion of the visual light region (400–800 nm) to obtain additional information. NIR signals yield information on the excitation of overtones and combination of molecular vibrations to higher energy levels. In this way, C–H, O–H and N–H bonds, which are found in large quantities in water, protein, carbohydrates and fat can be characterised. Thus, the NIR spectrum of any food can give a global signature of composition which, with the application of chemometric techniques (e.g. principal component analysis (PCA) and partial least squares (PLS) regression) can be used to elucidate particular compositional characteristics in the food matrix, not easily detected by targeted chemical analysis (Downey, 1994, 1996).

Several investigations have been performed using NIR spectroscopy to predict sensory attributes such as hardness, juiciness, tenderness, flavour and acceptability in both beef and pork meat (Brøndum et al., 2000; Ellekjaer, Isaksson, & Solheum, 1994; Hildrum, Nilsen, Mielnik, & Næs, 1994, 1995; Liu et al., 2003; Venel et al., 2001). However, practical use of NIR spectroscopy in dairies has mainly been restricted to measurements of moisture, fat, protein and amino acids in milk products (Adams, Latham, Barnett, & Poynton, 1999; Da Costa Filho & Volery, 2005; Frank & Birth, 1982; Hermida, Gonzalez, Sanchez, & Rodríguez-Otero, 2001; Karoui et al., in press; Skeie, Feten, Almøy, Østlie, & Isaksson, 2006). Only few reports have investigated the ability of NIR spectroscopy to predict some sensory parameters (Downey et al., 2005; Sørensen & Jepsen, 1998). However, in their studies, these latter have investigated cheeses (Cheddar and Danbo) which were manufactured at the pilot scale dairy plant. So, it would be interesting to validate the relevance of NIR spectroscopy to predict some quality attributes of cheeses manufactured by using different milks, starters and different cheese making procedures and originating from different European countries. The present study investigated the relationship between sensory analysis and NIR spectroscopy of 20 commercially Emmental cheeses produced in different regions around Europe. It will provide the basis for further studies involving other spectroscopic techniques (e.g. mid-infrared) or the combination of the NIR–MIR spectroscopies to be used for the analysis and measurements of sensory attributes in cheese.

2. Materials and methods

2.1. Origin and selection of the cheese samples

The geographic origin and the age of the cheeses investigated in this study have been reported previously by Pillonel et al. (2002). The number of Emmental cheeses considered in this study was 20 originating from six European regions: Allgäu (Germany), Bretagne and Savoie (France), Switzerland, Middle Finland, and Vorarlberg (Austria) (Table 1).

Three samples were chosen from each region, except for Switzerland with six samples and Finland with two samples. The samples were supplied directly by the cheese factories (Austria, Finland and Switzerland) or were collected with the help of a national dairy research centre (France and Germany). The samples (approx. 8 kg) were supplied as sectors or slices of a whole block. The first 2 cm from the rind were discarded. For analyses, where grated cheese was required, portions were cut across the whole block (height) to take into account concentration gradients. The cheeses investigated were chosen at ages between 2.5

Table 1
Origin and ripening time of the 20 investigated cheese samples

Samples (*n*)	Region (country)	Ripening time
3	Allgäu (Germany)	4
3	Bretagne (France)	2.5
6	Switzerland	4
2	Middle Finland	3
3	Savoie (France)	3
3	Vorarlberg (Austria)	3

and 4 months of ripening, which correspond to that sold in stores. For most regions, this corresponds to the average ripening time. In Switzerland, a four months old Emmental cheese is considered very young, since an important part of the market is made up of Emmental over 8 months old. We limited, however, our investigation to young Emmental Switzerland and the corresponding foreign samples since the percentage of confusion between these cheeses is highest. The investigated cheeses were packed in an insulated shipping container in dry ice and were available in the Federal Dairy Research Station (FAM, Liebefeld) within 2 days after being sent.

2.2. Sensory analyses

Fresh samples were analysed according to a protocol described by Lavanchy and Bütikofer (1999). This methodology was developed in the frame of an European programme for the sensory characterisation of hard and semi-hard cheeses. It describes the appearance and texture such as firmness, friability, elasticity and adhesiveness as well as olfacto-gustatory characteristics (salty, acid, sweet, bitter, intensity of odour and aroma). A 2–7 scale was used to evaluate the intensity of the attributes. The samples were evaluated by the accredited sensory panel of the Federal Dairy Research Station (FAM, Liebefeld). The mouths were rinsed with mineral water between samples.

2.3. Near infrared diffusion reflection

NIR spectroscopy was performed as described by Pillonel et al. (2003). The cheese samples were kept at −18 °C until analysis. Cheese samples were grated with a laboratory hammer and then approximately 150 g of grated cheese were placed in a glass Petri dish and measured by diffuse reflection on a Büchi NIRLab N-200 spectrometer (Flawil, Switzerland) using a rotating measuring cell. For each sample, 64 scans were recorded at 20 °C from 1000 to 2500 nm with a spectral resolution of 2.5 nm. For each cheese, three spectra were recorded at three different points by rotating the Petri dish.

2.4. Statistical treatment of data

2.4.1. Principal component analysis

PCA transforms the original variables (wavelengths or sensory attributes) into new axes called principal components (PCs), which are orthogonal, so that the data set presented on these axes are uncorrelated with each other. The PCA allow to observe the latent structures between the investigated variables. Two separate PCA were applied on the normalised sensory and NIR spectra. The NIR spectra were normalised by reducing the area under each curve to unity as described by Bertrand and Scotter (1992). This treatment allows to reduce the scattering effect since, mainly the shift of the maximum and the width changes of the spectra were considered (Karoui, Laguet, & Dufour, 2003). The PCA was performed by using StatBoxPro® software (version 5.0, Paris, France).

2.4.2. Partial least squares regression

The objective of this task was to build a statistical model for the prediction of cheese attributes on the basis of NIR spectra. Because the number of the wavelengths in the NIR spectra were much larger than the number of cheese samples in the data set, it was necessary to use multivariate statistical methods to validly extract information from the data set. Several statistical modelling techniques can be adopted for the proper calibration performance, such as the linear and nonlinear multiple regression analyses: principal component regression (PCR) and PLS. In the present study, PCA was carried out on the normalised data sets; the scores of each sample on the first 12 PCs were saved and these scores were then inputted into a PLS regression. Considering the first 12 PCs only was justified by the fact that they cover (12 PCs) the most variation contained in the raw data. This procedure has been applied previously by Adams et al. (1999) for the determination of moisture and fat contents of processed cheeses from NIR spectra. The above authors reported that the PLS regression cannot be applied in a straightforward way to raw NIR spectra because of the high correlations occurring between the wavelengths. Advantages were found in the preliminary transformation of the raw data into their PCs. As the number of observations was small (20 cheeses = 60 spectra), the regression models were validated by a leave one-out cross-validation. This cross-validation enables the dimensions of the predictive model to be chosen.

In order to compare between the different established models for a given variable, the values of the root mean square error of cross-validation (RMSECV) were considered. The performance of the models was quantified by determining the squared correlation coefficient (R^2) for predicted versus measured compositions in cross-validation and the ratio of standard deviation (SD) to RMSECV of data set. The ratio of the SD to the RMSECV, called the ratio of prediction to deviation (RPD), is the factor, by which the prediction accuracy has been increased compared to using the mean composition for all samples. This ratio is desired to be larger than 2 for a good calibration (Mouazen, De Baedemaeker, & Ramon, 2005). An RPD ratio less than 1.5 indicates poor predictions and the model can not be used for further prediction. Practical utility of the calibrations can also be assessed by using the range error ratio (RER) (Williams, 1987). This ratio is calculated by dividing the range of a given constituent by the prediction error for that constituent. PLS was performed using Unscrambler® software (version 7.8, Camo process AS, Norway).

2.4.3. Canonical correlation analysis

Canonical correlation analysis (CCA) is a multivariate treatment, which describes the correlation between two sets of variables recorded on the same samples (Devaux, Robert, Qannari, Safar, & Vigneau, 1993). It considers the correlations that exist between the two groups of variables and points out the most correlated variables. The procedure assesses linear combinations of the two groups of variables in a such a way that the correlations between these combinations are maximum. Although being a standard tool in statistical analysis, where canonical correlation has been used for example in economics and medical studies, only limited reports have been found in dairy industry (Karoui et al., 2003; Lebecque, Laguet, Devaux, & Dufour, 2001; Mazerolles et al., 2001; Mazerolles, Devaux, Dufour, Qannari, & Courcoux, 2002). CCA was applied to the scores of the first 12 PCs of the PCA performed on NIR and sensory data sets. CCA was carried out using STATGRAPHICS PLUS software (Statistical Graphics Corp., Englewood Cliffs, New Jersey, USA).

3. Results and discussion

To describe cheese quality as described by the consumer, sensory profiling using relevant descriptors are an appropriate approach. The use of suitable sensory vocabulary for profiling cheese is crucial to relate sensory characteristic to biochemical transformation in cheese. A summary of values obtained by the state panel for each of the 10 sensory attributes is shown in Table 2.

PCA was applied to the sensory data in order to investigate the relationships between the various variables. The obtained result was shown in Fig. 1. According to the principal component 1 (PC1) accounting for 37.6% of the total variance, attributes friability, acidity, aroma and saltiness were on the far right, whereas elasticity and sweetness were on the far left. Similarly, the attributes firmness and odour were opposite to the adhesivity according to the PC2 (Fig. 1).

Table 3 shows the Pearson correlation coefficients between the sensory properties measured for the investigated cheeses. A significant positive correlations ($P < 0.05$) were observed between the attribute friability and the following attributes: firmness, aroma intensity, odour intensity and acidity; between acidity and aroma intensity as well as between saltiness and aroma intensity; between saltiness and bitterness; between firmness and odour intensity and between acidity and saltiness. However, strong negative correlations were found between firmness and adhesivity, aroma intensity and elasticity and also between saltiness and elasticity (Table 3).

Table 2
Sensory attributes of European Emmental cheeses used in the calibration set for the PLS cross-validation models

Sensory attributes	Minimum	Maximum	Mean	SD	CV (%)
Appearance and texture					
Adhesivity	2.16	4.00	3.10	0.48	15.54
Friability	2.37	3.69	2.91	0.36	12.52
Elasticity	3.47	4.70	4.20	0.35	8.25
Firmness	2.53	5.10	3.79	0.61	15.99
Olfacto-gustatory characteristics					
Aroma intensity	2.58	4.00	3.13	0.33	10.47
Odour intensity	2.41	4.10	3.17	0.35	10.98
Bitterness	1.37	2.23	1.82	0.24	12.92
Saltiness	1.74	2.79	2.23	0.29	13.27
Acidity	1.84	2.95	2.18	0.28	13.00
Sweetness	2.23	2.90	2.60	0.20	7.81

SD, standard deviation; CV, coefficient of variation = 100 × [SD/mean].

3.1. Prediction of cheese sensory attributes from NIR spectra

Typical infrared spectrum of the investigated cheeses is shown in Fig. 2. The overtone and combination bands observed in the NIR spectra are due to the C–H, N–H and O–H bonds. Contributions from water absorption can be observed around 6800 and 5200 cm^{-1}. Two bands dominating the 4600–4200 cm^{-1} region are due the presence of CH_2 group of lipids and/or protein located at 4255 cm^{-1} and 4600 cm^{-1}. Other bands resulting from the terminal methyl groups were also present at approximately 8200 and 5800 cm^{-1}.

A summary of the predictive performances of the developed models for each of the 10 sensory attributes using the first 12 PCs is shown in Table 4.

The optimal number of the PLS factors for the prediction of the attribute adhesivity, firmness and sweetness was 2. For all other attributes, the optimal number was 1.

The best prediction of the investigated variables was obtained with appearance and texture attributes such as firmness and adhesivity since the R^2 of these latter was 0.82 and 0.72, respectively. Considering the olfacto-gustatory attributes, the highest R^2 was obtained for sweetness with an R^2 of 0.71. The liner regression plots of measured versus predicted firmness and sweetness sensory attributes are shown in Fig. 3a and b, respectively. From Fig. 3b, it appeared that Finnish cheeses were found in the top cluster along the regression line, while German cheeses were located in the bottom cluster.

Generally, it was assumed that the olfacto-gustatory data contained less structure than the appearance and texture data. This phenomenon has been attributed to the fact that the former contained shorter range of variation (Sørensen & Jepsen, 1998). These findings were in agreement with the present investigation since the standard deviation (SD) of olfacto-gustatory attributes varied in the range of 0.20–0.35, whereas those of appearance and texture were between 0.35 and 0.61 (Table 2).

Although, the investigated Emmental cheeses have different source of variability since they are manufactured from different European regions and produced with different milks (raw or thermised (63 °C, 30 s)), using different cheese-making procedures and exhibited different ripening time, the R^2, RPD and RER of the investigated attributes were better than those found with Downey et al. (2005) in Cheddar cheeses determined in the range of 750–1098 nm and of 1100–2498 nm. Indeed, in their research, the authors reported that the best prediction was found for the attribute

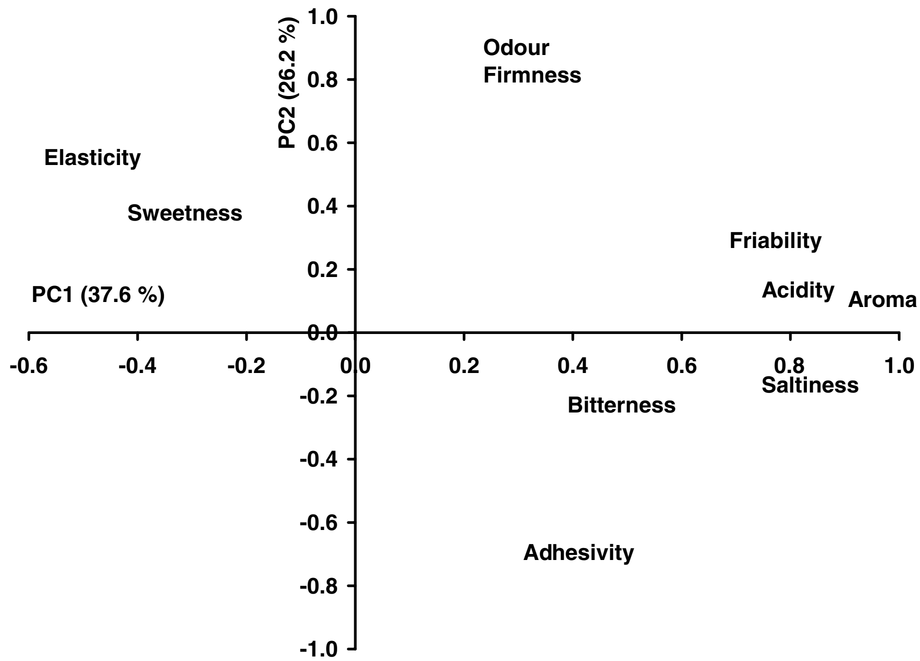

Fig. 1. Principal component analysis similarity map determined by principal components 1 (PC1) and 2 (PC2) of 10 sensory attributes.

Table 3
Pearson correlation coefficients ($P < 0.05$) between the sensory attributes of European Emmental cheeses

Sensory attributes	Adhesivity	Friability	Elasticity	Firmness	Aroma intensity	Odour intensity	Bitterness	Saltiness	Acidity	Sweetness
Appearance and texture										
Adhesivity	1									
Friability	0.31	1								
Elasticity	−0.42	−0.26	1							
Firmness	−0.53*	0.53*	0.32	1						
Olfacto-gustatory characteristics										
Aroma intensity	0.25	0.61*	−0.51*	0.29	1					
Odour intensity	−0.40	0.49*	0.25	0.71*	0.42	1				
Bitterness	0.41	0.05	−0.04	−0.19	0.40	−0.08	1			
Saltiness	0.36	0.42	−0.53*	0.06	0.74*	0.07	0.51*	1		
Acidity	0.21	0.56*	−0.37	0.38	0.77*	0.26	0.38	0.78*	1	
Sweetness	−0.39	−0.32	0.34	0.02	−0.23	0.24	−0.08	−0.22	−0.24	1

* Significant difference ($P < 0.05$).

crumbly ($R^2 = 0.75$, RPD = 2 and RER = 8.77) and ($R^2 = 0.61$, RPD = 1.63 and RER = 7.1) in the range of 750–1098 nm and of 1100–2498 nm, respectively. The same researchers measured also the attribute firmness judged on the first chew using the front teeth with $R^2 = 0.41$, RPD = 1.28 and RER = 5.1 in the measurement range of 750–1098 nm. In the present study, the prediction of the attribute firmness was more accurate than that found with Downey et al. (2005) since the $R^2 = 0.82$; slope = 0.85, RPD = 2.42 and RER = 10.26. Additionally, Sørensen and Jepsen (1998) measured the attributes acidity ($R^2 = 0.59$) and sweetness ($R^2 = 0.38$) of semi-hard (Danbo) cheeses using NIR with a degree of success less accurate than that achieved in this study. The obtained results could be considered as promising. However, more research will be needed to validate the accuracy of NIR technique for the prediction of the investigated sensory attributes.

It is well known that a number of criteria should be considered in order to assess the utility of the calibration models. These include the R^2, RMSECV, RER and RPD, as explained in Section 2. The RMSECV for the attributes adhesivity, friability, elasticity and firmness was 0.25, 0.25, 0.20 and 0.25, respectively. These RMSECV values resulted in RER values of 3.59, 5.22, 6.26 and 10.26, respectively, suggesting that the model might have practical utility in the industry for the attributes friability, elasticity and firmness. The olfacto-gustatory attributes might also have practical utility since the RER was higher than 5 (Table 4).

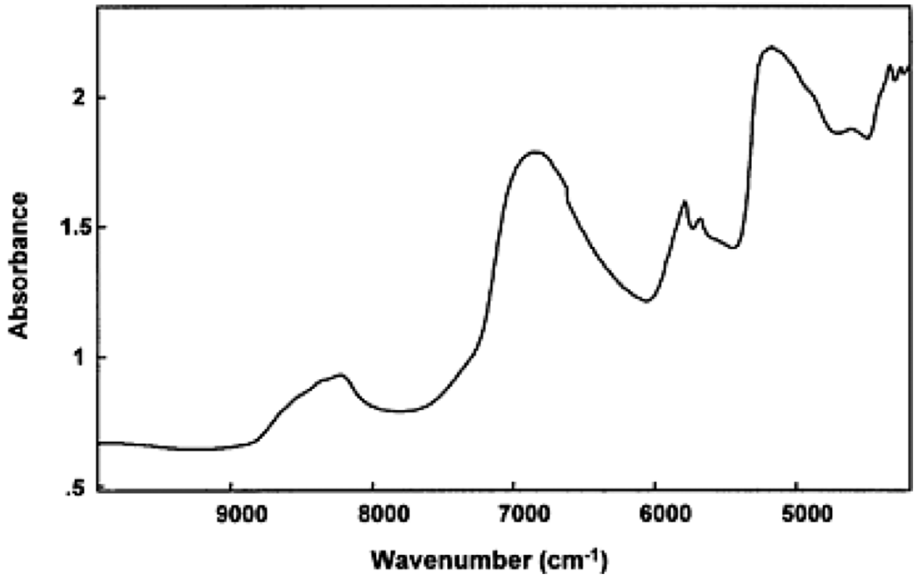

Fig. 2. Typical infrared spectrum of the investigated cheeses.

Table 4
Cross-validation results of NIR models developed with of the PLS cross-validation regression

Sensory attributes	LV	R^2	Slope	RMSECV	RPD	RER
Appearance and texture						
Adhesivity	2	0.72	0.76	0.25	1.92	3.59
Friability	1	0.49	0.48	0.25	1.44	5.22
Elasticity	1	0.68	0.59	0.20	1.77	6.26
Firmness	2	0.82	0.85	0.25	2.42	10.26
Olfacto-gustatory characteristics						
Aroma intensity	1	0.60	0.55	0.20	1.62	7.00
Odour intensity	1	0.32	0.35	0.28	1.24	6.03
Bitterness	1	0.63	0.57	0.14	1.66	6.07
Saltiness	1	0.53	0.50	0.20	1.49	5.26
Acidity	1	0.63	0.57	0.17	1.67	6.52
Sweetness	2	0.71	0.76	0.11	1.89	6.23

Abbreviation: LV, latent variables; R^2, coefficient of determination; RMSECV, root mean square error of cross-validation; RPD, ratio of prediction deviation (Standard deviation/RMSECV); RER, range error ratio (maximum–minimum/RMSECV).

It has been reported in previous investigations that the predictive information related to sensory properties and NIR spectra did not seem to be related to a specific chemical moiety in the sample (Byrne, Downey, Troy, & Buckley, 1998; Hildrum et al., 1995) and it was not clear which particular spectral information was related to a specific sensory property. Recently, it has been reported that correlations between NIR spectroscopy and sensory properties might be caused by collinearity between compositional variables, between wavelengths or between other sensory properties as has been reported by Martens and Martens (2001). Selection of particular regions of the spectra proved to have large effects on the calibration results as has been stated by Downey et al. (2005).

The ability of the NIR models to differentiate between a range of sensory properties in the present investigation is likely to be related to overall differences in the cheese matrix among the samples in the set, which presumably relates to the multiplicity of differences among the samples, including variety, region of origin, manufacturing process, quality of milk and the age of cheese. However, the results obtained in the present investigation could be considered as promising. Indeed, up-to-date, cheese ripening is a food process not highly automated, for which the quality of the final products depends on the know-how and the skills of the cheese maker. In regards to this concept, the work conducted in the present study could bring information to the cheese maker about the evolution of sensory attributes during ripening. However, more research is needed in order to test the ability of NIR to predict some sensory attributes at different ripening stages.

3.2. Canonical correlation analysis of NIR and sensory data sets

Correlations between the sensory attributes and NIR data were investigated in order to get a better insight into the relationships between the characteristics at macroscopic and molecular levels of the investigated cheeses. The CCA allowed to give an R^2 of all the investigated variables. It has been successfully applied for comparing fluorescence and mid-infrared spectra of semi-hard cheeses (Mazerolles et al., 2001, 2002) and fluorescence and sensory data sets of Salers cheese (Lebecque et al., 2001). In both cases, the authors were able to provide relevant similarity maps of the samples that were not immediately found by PCA. The CCA can be applied when the same samples were characterised by two different techniques. Ten pairs of canonical variates were used to study the correlation between sensory and NIR data sets.

CCA assessed eight canonical variates for both the NIR spectra and sensorial attributes. The correlation coefficients

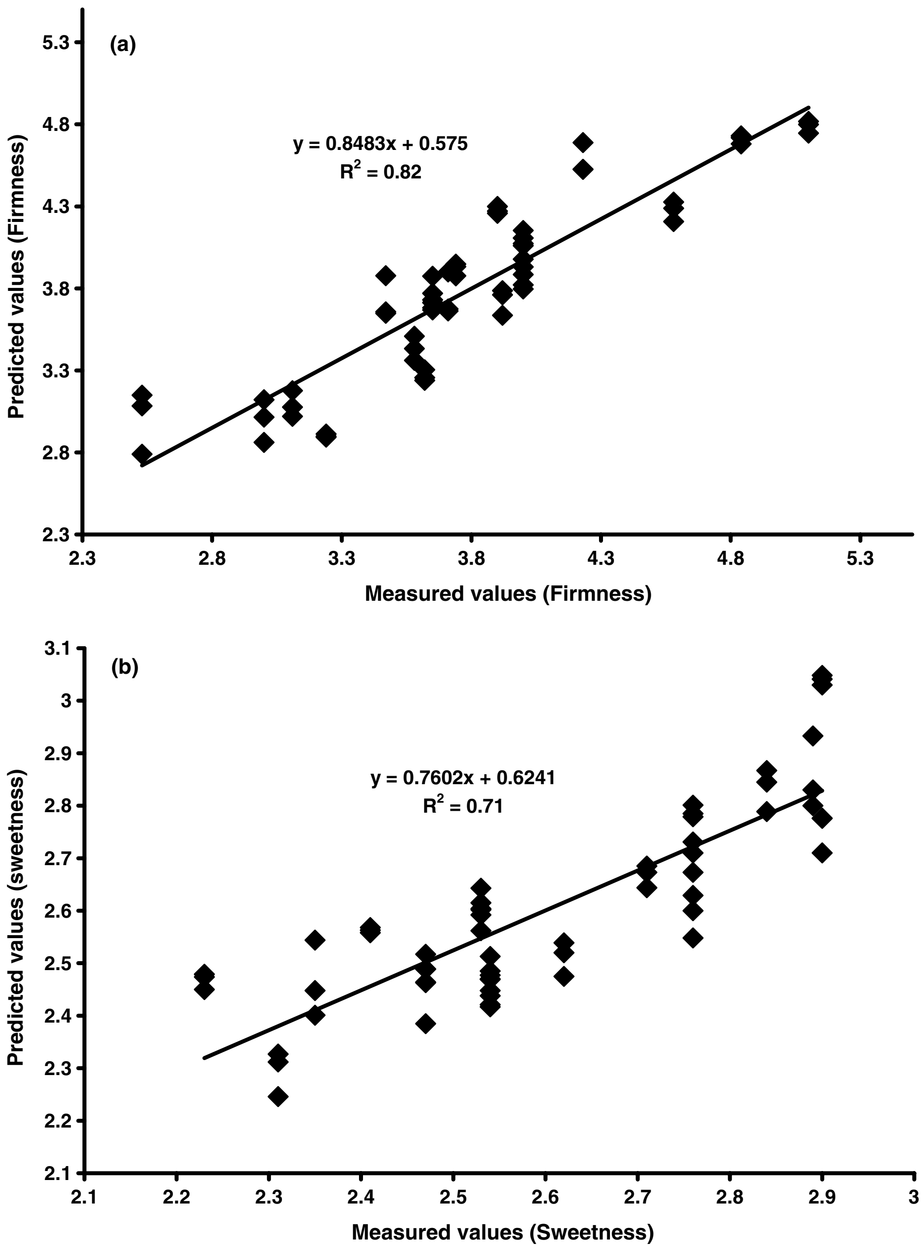

Fig. 3. Linear regression plot of measured versus predicted firmness: (a) and sweetness, (b) sensory attributes.

(R^2) between the NIR canonical variates and the sensorial corresponding ones were 0.99, 0.99, 0.95, 0.91, 0.72, 0.65, 0.49 and 0.29, respectively. The correlations obtained indicated that the 8 first canonical variates provided a common description of the samples both from NIR and sensory analysis. As the two techniques provided similar results, it was concluded that NIR spectroscopy allowed good characterisation of European Emmental cheeses.

The similarity maps for the CCA analysis performed on NIR spectral data and the sensory data are shown in Fig. 4a and 4b. Fig. 4a showed that French (Savoie and Bretagne) and Finnish cheeses were well separated from the other cheeses. Although, the other cheeses were slightly overlapped on the map, a trend to a good separation between these latter was observed. The results obtained from CCA were better than those obtained on NIR or sensory data sets (data not shown).

Considering the sensory attributes explaining the samples discrimination according to canonical variates 1, adhesivity, saltiness, elasticity and firmness had positive score values, while sweetness, friability had negative scores (Fig. 4b). The canonical variates 2 exhibited positive score values for the attributes sweetness and friability and negative values for acidity, bitterness and adhesivity. The obtained results were quite similar to those obtained with sensory data sets (Fig. 1); however, a better trend was obtained with CCA similarity map.

As the two methods allowed the discrimination of the investigated cheeses, it is suggested that the changes observed at the molecular and macroscopic levels were

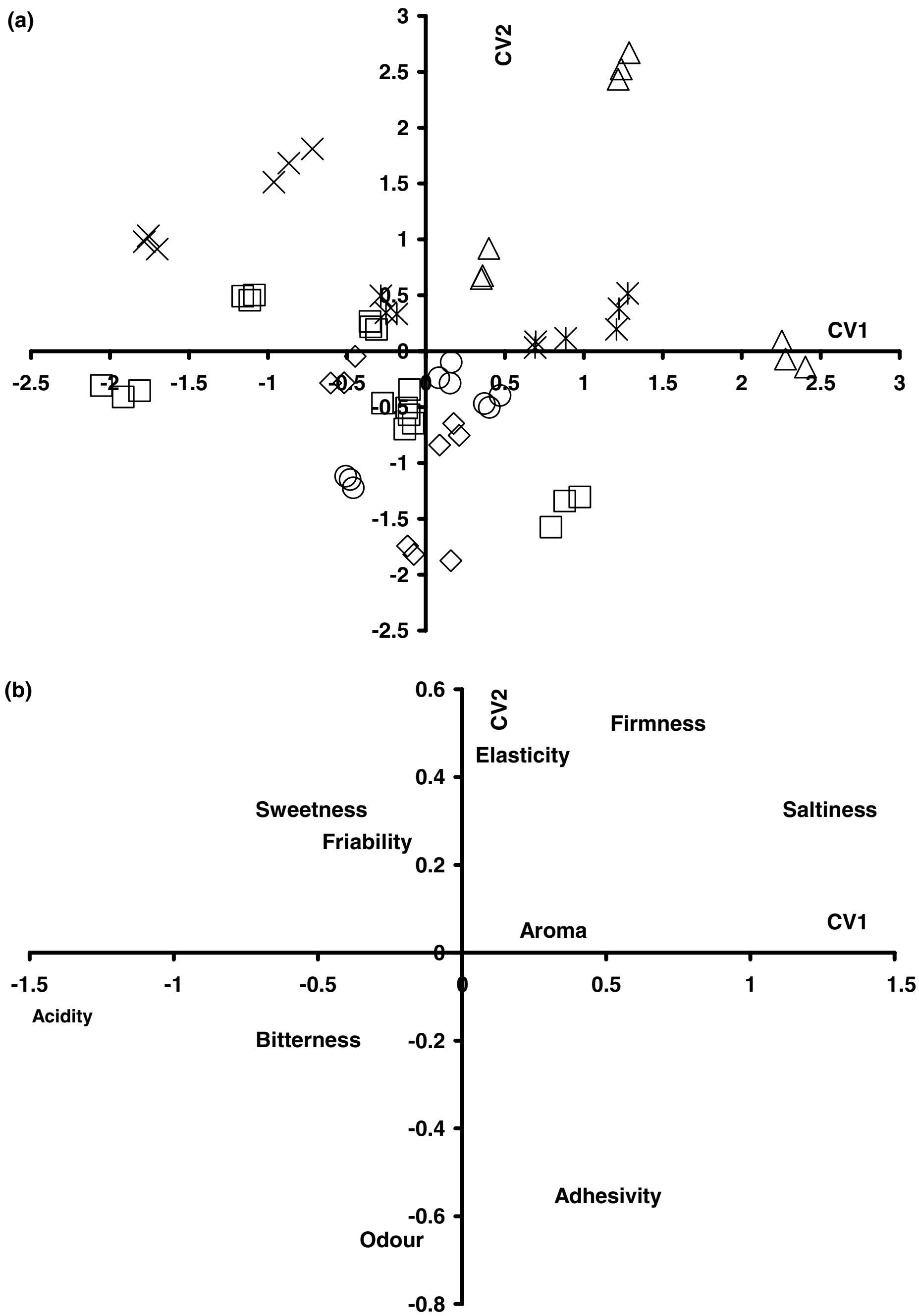

Fig. 4. Canonical correlation analysis similarity map determined by the canonical variates 1 and 2 for (a) near infrared data and (b) sensory attributes of Emmental cheeses produced in Germany (◇), Switzerland (□), France: Bretagne (△), Finland (×), France Savoie (∗) and Austria (○).

related to the texture of cheeses. Indeed, as the NIR spectra were normalised, the spectral information involved in the canonical variates 1 and 2 were related to the protein structures and interaction in the cheese matrix.

4. Conclusion

This study demonstrated the feasibility of NIR spectroscopy to predict some sensory attributes (e.g. adhesivity, firmness and sweetness) of Emmental cheeses originating from different European regions. However, the limited number of samples available in the present study leads us to be cautious concerning the potential of NIR spectroscopy. Indeed, with only 20 Emmental cheeses, the current models were still not very robust and further research that should include a high number of this cheese variety is needed. This would allow the inclusion of more variability of the sensory attributes and thus developing general mathematical models for better accuracy of the NIR technique. The simplicity of the method considering NIR spectroscopy offers rich opportunities for efficient characterisation of cheeses at a very low cost. In addition, the NIR spectroscopy has the potential of dramatically reducing the time when looking at time needed by the sensory panel. This study showed also that NIR spectroscopy is not only applicable for the determination of some chemical parameters of the same variety of cheeses produced in different European geographic origins (Karoui et al., in press), but may also provide a promising tool for the prediction of some sensory attributes.

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