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A VOLTAMETRIC E-TONGUE TOOL FOR THE EMULATION OF THE SENSORIAL ANALYSIS AND THE DISCRIMINATION OF VEGETAL MILKS.

Lluis Pascual[a], Marisa Gras[b], Daniel Vidal[b], Miguel Alcañiz[a], Ramón Martínez-Máñez[a,c] , Jose V. Ros-Lis[c,d*]

[a] *Instituto Interuniversitario de Investigación de Reconocimiento Molecular y Desarrollo Tecnológico. Universitat Politècnica de València - Universitat de València. Camino de Vera s/n, 46022, Valencia, Spain*

[b] *Instituto de Ingeniería de Alimentos para el Desarrollo. Universitat Politècnica de Valencia. Camino de Vera s/n. Valencia (Spain).*

[c] *CIBER de Bioingeniería, Biomateriales y Nanomedicina (CIBER-BBN).*

[d] *Departamento de Química Inorgánica. Universitat de València. Doctor Moliner 50, Burjassot (Spain).*

**Corresponding author. Tel: +34 963870000. Email: J.Vicente.Ros@uv.es*

ABSTRACT

The relevance of plant-based food alternatives to dairy products, such as vegetable milks, has been growing in recent decades, and the development of systems capable of classifying and predicting the sensorial profile of such products is interesting. In this context, a methodology to perform the sensorial analysis of vegetable milks (oat, soya, rice, almond and tiger nut), based on 12 parameters, was validated. An electronic tongue based on the combination of eight metals with pulse voltammetry was also tested. The current intensity profiles are characteristic for each non-dairy milk type. Data were processed with qualitative (PCA, dendrogram) and quantitative (PLS) tools. The PCA statistical analysis showed that when using three first principal components, which covered 77% of variance, the eight samples can be differentiated, and the preparation method (artisanal milks or commercial) is one of the main differentiation factors, together with raw material type. The

PLS statistical analysis allowed models to be created to predict all 12 sensorial parameters. The goodness of the predictions depends on the parameter being particularly accurate for the body, the granularity in the wall of glass and homogeneity of colour. The results strongly suggest the potential feasibility of using electronic tongues as systems for easy, rapid and effective sensorial assessments of vegetable milks.

Keywords: vegetable milk, tiger nut, electronic tongue, sensorial analysis

1.- INTRODUCTION

The relevance of plant-based food alternatives for dairy products, such as vegetable milks based on soya, almond, rice or oats, has been growing in recent decades. Compared with milk, they are perceived by consumers as healthier food products that allow the intake of calcium and proteins with no exposure to lactose (to which some people are intolerant) or animal fat (that increases cholesterol levels and the risk of cardiovascular diseases) (Bernat et al., 2014). They are also excellent substrates to develop dairy products or ice creams with probiotics (Aboulfazli et al., 2014; Aboulfazli et al., 2016). Finally compared with animal milk, vegetable milks are advantageous from an environmentally point of view as the carbon footprint of growing vegetables is lower than that of cattle (Mikkola et al., 2014). These advantages have the drawback that such materials, i.e. soya or almonds, are qualified as allergens. Therefore, the control of food fraud is most relevant from both the economic and food safety viewpoints. Together with conventional raw materials, such as soya, almond, oat or rice, vegetable milks can also be prepared with other highly relevant materials, like tiger nuts.

The properties of non-dairy milk products, and therefore their sensorial characteristics, depend on both the raw material and the processing procedure. For example, industrial and artisanal milks can seem diverse, even if they are made with the same kind of vegetables. The origin of the raw material can affect the taste of drink and its nutritional characteristics (Kaneko et al. 2011).

One of the most innovative and potent techniques to analyse or classify foods is to use electronic tongues and noses (Tahara and Toko, 2013; Loutfi et al., 2015; Peris and Escuder, 2016). Electronic tongues attempt to mimic chemical senses. The main goal is to sense complex media, in which thousands of chemical compounds interact, and to determine certain parameters of interest. Gardner and Bartlett (1994) defined the electronic nose as an instrument that comprises an array of electronic chemical sensors with partial specificity, with an appropriate pattern recognition system capable of recognising simple or complex odours. Electronic tongues are similar systems used to recognise liquids (Legin et al., 2002).

Sensing strategies in electronic tongues and/or noses include potentiometric and voltammetric electrodes, metal oxide semiconductors (MOS), the quartz crystal microbalance (QMB), conducting polymers (CP) and surface acoustic wave sensors (SAW). Voltammetric sensors are advantageous devices for multicomponent measurements thanks to their high selectivity and sensitivity, high signal-to-noise ratio, low limits of detection, and their various measurement modes (square wave, large pulse voltammetry, cyclic voltammetry, etc.). Electronic tongues are based on combining diverse sensors and, for voltammetric electronic tongues, each sensor collects dozens to hundreds of current samples. This generates vast amounts of data that must be processed by multivariate analysis tools. Principal components analysis, neural networks, partial least squares, clustering and dendrograms are among the most widely used pattern recognition methods (Ciosek and Wroblewski, 2007).

E-tongues are devoted mainly to the automatic analysis of complicated composition samples, to recognise their characteristic properties and to do fast qualitative analyses. A device is named ‘a taste sensor’ when it is used to classify basic taste sensations, and the results are compared with a human panel.

Among the reported uses of e-tongues in the food industry, we find examples in almost any liquid food. E-tongues have been used for quality controls during production and storage (mineral waters, wine, coffee, milk, juices), for the optimisation of bioreactors, ageing process controls (cheese, whiskey) and automatic controls of taste (wine, juices, water, milk, honey, etc.) (Ciosek and Wroblewski, 2007; Tahara and Toko, 2013; Loutfi et al., 2015; Peris and Escuder, 2016). In particular they have been applied for recognition, categorization as well as identification purposes of milk and dairy products (Ciosek, 2016) in areas such as process control, analysis of flavour, microbial growth monitoring, quality control studies, classification of milk samples (Ciosek et al., 2006; Bougrini et al., 2014), freshness evaluation (Winquist et al., 1998) and detection of adulteration or residues (Dias et al., 2009; Wei and Wang, 2011; Hilding-Ohlsson et al., 2012). However, as far as we are aware, e-tongues have not been explored as taste sensors to predict sensorial analyses in vegetable milks.

Based on these concepts, we report herein the validation of a sensorial methodology based on 12 attributes to perform the sensorial analysis of vegetable milks (oat, soya, rice, almond and tiger nut). An electronic tongue based on the combination of eight metals with pulse voltammetry was also tested.

2.- MATERIALS AND METHODS

2.1.- Materials

Commercial vegetable milks (soya, oat, rice almond and two kind of tiger nut) were acquired from a local retailer. They were UHT, conserved at room temperature and used immediately after opening.

2.2.- Preparation of artisanal tiger nut milk

To prepare the artisanal tiger nut milk, 1 kg of dry tiger nuts from Valencia (Spain) or Burkina Faso were immersed in a 15% NaCl solution in water for 3 h, and water was changed every 45 minutes.

Then the hydrated tiger nuts were filtered and immersed in a hypochlorite solution (2%) for 30 minutes to ensure the food safety of the final product. The resulting material was filtered and washed repeatedly with water to eliminate any hypochlorite remains. Tiger nuts were ground, 2-3 litres of water were added and the resulting suspension was filtered by collecting a white liquid. To the remaining solid, 2-3 litres of water were added. After filtering the liquid was collected together with the first extraction. Next 825 g of sucrose and water were added to acquire 6 litres to obtain the tiger nut milk, which was bottled and stored under freeze conditions until measured.

2.3.- Acquiring the sensorial profile

The characterisation of organoleptic properties was based on 12 attributes (see Table 2). These parameters were defined for tiger nut milk by Altarriba (1994), following the recommendations of Directive ISO/TC 34/SC 12 N254 (currently ISO 13299:2016 Sensory analysis -- Methodology -- General Guidance for Establishing a Sensory Profile). Drinks were tested in duplicate by a panel formed by 45-57 semitrained panellists, who had to score each drink for all 12 attributes on a non-structured 1-10 scale with the extremes coded by the topics defined in Table 2; e.g., for colour, extremes were light beige and dark beige. With major or minor frequency, all the members of the panel used to consume tiger nut milk, a very known local drink. In addition, they took part in a previous training session, during which the 12 attributes were described, and panellists valued them tasting 3 tiger nut milks, 2 commercial (different brands) and 1 artisanal.

2.4. Electronic Tongue Based on Pulse Voltammetry

The electronic tongue device used in this work consisted of an eight working electrodes array (Au, Pt, Rh, Ir, Cu, Co, Ag and Ni) with 99.9% purity and a 1-mm diameter, from Sigma-Aldrich housed inside a stainless-steel cylinder used at the same time as both the electronic tongue system body and the counter-electrode. The different wire electrodes were fixed inside the cylinder with an epoxy RS 199-1468 polymer (Campos et al., 2013). A combination of noble (i.e., Au, Pt Rh and Ir) and non-noble electrodes (Cu, Co, Ag and Ni) was selected to combine the response that derived from the redox reactions, adsorption of the chemical species on the electrodes' surface and the potential chemical reactions between species in both the solution and oxidised metal.

A Saturated Calomel Electrode (SCE) was used as a reference electrode. Before use, the electrode surface was prepared by polishing as indicated in reported procedures (Campos et al., 2013).

The electronic tongue was controlled with a home-made software application that runs on a PC and home-made electronic equipment, developed at the Instituto de Reconocimiento Molecular y Desarrollo Tecnológico (IDM) of the Universidad Politécnica de Valencia (UPV - Spain) (Bataller et al., 2013). This equipment is able to generate a sequence of up to 50 pulses with an amplitude and width that fell within the range of [-2V to +2V] and [1 ms to 800 ms], respectively. A different pulse pattern can be configured for each working electrode.

This study employed a Large Amplitude Pulse Voltammetry (LAPV) wave form (Winquist et al., 1999; Gutés et al., 2006). Figure 1 shows the applied pulse pattern, which consisted of 41 pulses of 50 ms in a similar configuration to a staircase voltammetry, but the potential was set at 0 after each increment. The pulse sequence ranged from -1000 to 1000 mV for the noble metals and from -500 to 500 mV for the non-noble metals, with increments of 200 or 100 mV, respectively. Maximum and minimum potentials were chosen to avoid water electrolysis phenomena. Figure 1 illustrates the intensity/time diagram for the commercial tiger nut milk TNA, where silver was the working electrode, which overlapped the applied potential. All the measurements were carried out the same day. First, 8 samples corresponding to each one of the milks were measured in random order; then the same process was repeated two more times, so that 3 replicates were obtained for each milk type. The software application was configured to perform five consecutive iterations for each sample; i.e., the pulse pattern was applied to the eight working electrodes and the test was run 5 times before the sealed measuring environment had to be opened to discard the sample and to prepare a new one. The resulting data contained 984 current values for each applied pulse array (24 points per pulse × 41 pulses) and 39,360 currents (984 current values× 8 electrodes x 5 iterations) were recorded per sample. Thus the electronic tongue dataset for the discriminant and quantification studies contained 944,640 points (8 samples x 3 replicates × 39,360 current values).

2.5. Data analysis

The raw data of the sensory analysis were pre-processed to detect outliers using statistical descriptive analysis (boxplots). If any of the 12 scores granted by a judge to a drink was identified as an outlier, the whole set of scores was eliminated. As a result, 10 of the 411 sensorial measurements were discarded (8 corresponding to the soybean drink and 2 to the Burkina Faso tiger nuts milk). An ANOVA applied to the sensorial data detected some significant nonnormality in the data, which violates the assumption that the data come from normal distributions, so the Kruskal-Wallis test was performed to compare the medians instead of the means. To determine which medians are significantly different from which others, the median notch option of the Box-and-Whisker Plot was selected from the list of Graphical Options. These analyses were performed using the Statgraphics software. Compromise scores were calculated following the STATIS methodology (Meyners et al., 2000; Meyners, 2003)

Multivariate data analysis (MVDA) tools were used to process both sensorial and electronic tongue data using Solo software (Eigenvector Research Inc., Wenatchee, WA, USA). A principal component analysis (PCA) is an example of such an MVDA that uses variance in experimental data to produce a score plot that identifies differences between observations or experiments, which can be used to classify or group observations. PCA decomposes the primary data matrix into a new set of orthogonal variables called principal components (PCs) which are linear combination of the original variables. The first principal component (PC1) is the dimension along which observations are maximally separated or spread out. The second principal component (PC2) is the linear combination with maximal variance in a direction that is orthogonal to the first principal component, and so on. Scores are the coordinates of the samples in the new principal component space while loadings correspond to the coordinates of the principal components in the old variable space. In this study, PCA was applied to sensorial and electronic tongue data. In the case of electronic tongue data, diversity among samples was also assessed by an unsupervised hierarchical cluster analysis (HCA) with the input data, and Ward's method as it minimises the total within cluster variance.

Partial Least Squares Regression (PLSR) is a type of MVDA employed for the generation of quantitative prediction models. PLSR is a multivariate projection method used to find the components of the matrix of input X that describe relevant variations in input variables, while achieving the highest correlation with the objectives (Y) and providing the lowest weight to variations that are irrelevant or related to noise at the same time. Prediction models are obtained by applying a multiple linear regression to these components, called latent variables. Prediction models are built using a calibration set of samples and validated on a different group of samples (validation set). PLSR was applied to electronic tongue data to generate prediction models for every sensorial parameter.

Before applying PCA, HCA and PLSR the dimension of the electronic tongue data matrix was reduced by averaging the 5 iterations of each measurement. Therefore, the size of the data matrix prior multivariate data analysis was 188,928 points (8 samples x 3 replicates × 8 electrodes x 984 current values).

Data were pre-processed by autoscaling (mean centre and unit standard deviation) before MVDA. For PLSR studies, two replicates for each milk type were selected randomly to build the model (calibration set) and the third replicate was used for validation. The number of latent variables used for each PLSR model was established after the corresponding cross-validation study using a venetian blinds method.

3.- RESULTS AND DICUSSION

3.1.- Sensorial studies

ISO 13299:2016 provides guidelines about the overall process for establishing a sensory profile. Sensory profiles can be established for all products or samples, which can be evaluated by these senses: sight, smell, taste, touch, hearing (e.g. food, beverage, tobacco product, cosmetic, textile, paper, packaging, air sample, water, etc.). Some sensory profiling applications are used to compare a product with other similar products or to map a product's perceived attributes to relate them to factors that can be instrumental, chemical or physical properties, and/or to consumer acceptability. We used a sensory profiling methodology for the vegetable milks based on 12 relevant sensorial parameters, which are found in Table 2 (Altarriba, 1994).

Means and standard deviations of the sensory panel data for the eight samples (soya, oat, rice, almond and four tiger nut drinks) are shown in Table 3a. As an ANOVA detected some significant nonnormality in the data, the Kruskal-Wallis test was performed to compare the medians, and the median notch option of the Box-and-Whisker Plot was used to determine which medians are significantly different from which others (P-value < 0.05). Results are shown in Table 3b. Furthermore, compromise scores were calculated using the STATIS methodology (see table S1 in the electronic supplementary material) with values similar to those collected in table 3a. As expected, the main scores for the aroma of tiger nut (AROMA) and for the typical flavour of tiger nut (TYPFLAV) were obtained by the four tiger nut milks, though TNB and OAT do not differ significantly with respect to AROMA (TNA, VLC and BFA reached the highest values), and BFA and ALMOND do not differ significantly with respect to TYPFLAV (VLC, TNA and TNB were better valued). For these parameters, soya and rice drinks obtained lower scores. We must consider that sweetness is a highly relevant parameter and soya milks are generally salty, and thus obtain lower values for the SWEET parameter. BODY, FILMWG, GRANWG are generally higher for the tiger nut milks. It was difficult to draw any conclusions for all the other parameters, although the vegetable milk prepared with the tiger nuts from Burkina Faso obtained the highest scores for OLDFLAV, RESFLAV, ROUGH and STRANGE. This indicates that the origin of raw material seems an important factor.

A correlation study for the attributes was performed and correlation coefficients higher than 0.85 were obtained for the following pairs: BODY-FILMWG, BODY-GRANWG, FILMWG-GRANWG and OLDFLAV-STRANGE. Also the pair AROMA-HOMCOL showed a high negative correlation coefficient (-0.88).

In order to obtain broader knowledge of the similarities among the diverse vegetable milks, a PCA was run with the sensory panel data offered in Table 3a. PCA was used here as a simple method to project data on a three-dimensional plane (Figure 2-A). The three first principal components explained 89.1% of variance, and five PCs were needed to explain at least 95% of variance (97.8%). As shown in Figure 2-A from the first three PCs, samples are well distributed in space, which confirms the feasibility of the selected sensorial parameters and the scales used to differentiate the diverse vegetable milks. As expected, three of the tiger nut milks (TNA, TNB and VLC) come close to one another and can be grouped together. Conversely, despite BFA being prepared from the same vegetable product, it is sited far from the others and consistently with the higher scores found for some parameters.

Figure 2-B shows the loadings plot of the sensorial data PCA. As expected, attributes identified as highly positively correlated in the correlation study (BODY-FILMWG-GRANWG and OLDFLAV-STRANGE) are located close to each other. Those sensorial parameters could be considered related to the textural properties of the drinks. Differences in the complexity of the carbohydrates of the raw materials could explain in a certain degree the differences in textural properties perceived by the panellists (Prachayawarakorn et al., 2016). AROMA and HOMCOL, with a high negative correlation coefficient, are located in opposite sides of the loadings plot.

3.2.- The PCA statistical analysis of the data collected with the electronic tongue

The intensity data collected with the electronic tongue in the different vegetable milk samples were analysed by PCA (Figure 3). The PCA study of the full set of data revealed a high degree of dispersion among the independent dimensions, created by the linear combinations of the electrochemical responses of the eight employed electrodes. The first principal component explained only 35.48% of variance of the data. The first two components represented 65.06% of total variance. The first five PCs explained 77.14 % of variance, but nine PCs were needed to account for 95% of variance. This high dimensionality helped to discriminate among highly related samples (e.g., different kinds of milk, forms of preparation or origin of raw materials). Although many dimensions are required to explain total variance, the PCA captured 77.14% of the variance observed in the experiment in the first three PCs, which are plotted on the X-, Y- and Z-axes, and represent the largest fraction of overall variability in the samples. Figure 3 shows the resulting PCA for the eight samples (three replicates) using all the electrodes and the collected data. It was possible to discriminate among the diverse vegetable milks, and replicates remained together.

Initially, three groups were created: we can see that the artisanal VLC and BFA are clearly closer from the e-tongue perspective (low values for PC1 and PC2), and more than initially expected bearing in mind the results noted above with the sensorial analysis. SOY is placed in the sector with high values for PC1 and with low values for PC2. The other commercial samples are sited round the zone with high PC2 values, but it is possible to discriminate among them, mainly due to PC3, as they are placed along the vertical axis (Figure 3). This is a promising result and suggests that the voltammetric electronic tongue presented herein can be a suitable tool to classify vegetables milks. Similar results were obtained with the HCA (Figure 4), which give a perfect clustering of the replicates of each sample, and the main differences are found between artisanal and commercial milks. Soya milk presents the biggest difference. Of all the other vegetable milks, those based on tiger nuts are clustered closer than the rest.

3.4.- PLS studies

The PCA study and the dendrogram show that the data obtained with the electronic tongue clustered according to kind of vegetable milk help to obtain a good classification model. In this section, we were also interested in analysing whether the data from the electronic tongue could be used to predict sensorial parameters in vegetable milks. In order to achieve this goal, the partial least square regression technique was used.

A PLS prediction model for each sensorial parameter was created with the intensity data obtained from the electronic tongue. Statistical models were validated for all the sensorial parameters (Table 4). By way of example, Figure 5 shows the PLS graph in which the measured *vs.* the predicted values of BODY (Fig. 5a), HOMCOL (Fig. 5b) and GRANWG (Fig. 5c) are plotted. Hence the measured values represent the real sensory score, while the predicted values are the values calculated according to the PLS algorithm using the electronic tongue data. Both the measured and predicted values are plotted together to evaluate the accuracy and precision of the created prediction models. A preliminary evaluation can be made by visually inspecting the difference between the measured and predicted values. Ideally, the predicted values should lie along the diagonal line to indicate that the predicted and actual values are the same. A more rigorous analysis can be done from the adjusting parameters. Table 4 offers the adjusting parameters for all the PLS prediction models which includes the number of latent variables used in the model, the coefficient of determination (R^2), the root mean squared error of prediction (RMSEP), the slope and intercept of the regression line (a and b) and the range of the predicted parameter. As we can see, all the sensory parameters can be predicted, but the quality of models strongly depends on the parameter. Although samples were complex and it was difficult to determine the factors that influenced the quality of predictions, some conclusions were reached. For example, BODY, HOMCOL and GRANWG with R^2 values of 0.957, 0.940 and 0.975, respectively, which were all relative to milks' physical characteristics, were especially well predicted by the electronic tongue-multivariate analysis combination. On the contrary STRANGE, OLDFLAV and TYPFLAV (R^2 values of 0.463, 0.549 and 0.710, respectively), which are highly subjective parameters related with aroma, showed a poor correlation. Surprisingly, SWEET was not found in any of the best predicted parameters, which agrees with the concept that the sweetness perceived in a drink depends not only on the amount of sugar, but also on other vegetable milk characteristics. In fact BFA and VLC were prepared by adding the same amount of sugar, but perceived sweetness (see Table 3) was completely different.

PLSR results were consistent with the conclusions of the correlation study. BODY, FILMWG and GRANWG presented a high correlation and show prediction models with similar quality. The same applies to AROMA and HOMCOL that are highly negatively correlated. Finally, other two highly correlated attributes as OLDFLAV and STRANGE present poor results in the validation of their respective PLSR models.

Also, PLSR models using the compromise scores were calculated for each sensorial parameter (electronic supplementary material, tables S2a and S2b). In general, the adjusting parameters are close to those calculated using the mean values, as expected from the fact that both values were similar. It offers only minor improvements in the training set, none of them offered an increase of R^2 higher than 0.015, and in most cases the accuracy of the fit is reduced. However, in the validation set diverse sensorial parameters showed an increase of R^2 higher than 0.05 (STRANGE, TYPFLAV and OLDFLAV). Thus, it ciould be a valid approach for some sensorial parameters.

Bearing in mind the prediction results in the studied sensorial parameters and their relevance to establish the organoleptic profile, the obtained PLS studies results confirmed the potential usefulness of electronic tongues to assess the sensorial profile of vegetable milks.

4.- CONCLUSIONS

The sensorial test based on 12 parameters proved useful for the characterisation of diverse vegetable milks. A simple electronic tongue based on metallic electrodes and pulse voltammetry was used to classify vegetable milks and to predict sensorial parameters. The system was based on the combination of eight metals with 41 pulses of potential. It was able to differentiate among the vegetable milks prepared with five raw materials (rice, almond, oat, soya and tiger nuts) by distinct procedures (artisanal or industrial) and of diverse origins (tiger nuts from Spain and Burkina Faso).

The dendrogram results validated our approach as differences among samples were bigger than among replicates. The main differences appeared between the artisanal and industrial vegetable milks and tiger nut milks were more similar to one another than the other vegetable milks. Electrochemical measurements were also taken to create PLS models in order to predict all 12 sensorial parameters. The goodness of the predictions depends on the parameter, and is particularly accurate for the body, the granularity in the wall of glass and homogeneity of colour. The results strongly suggest the potential feasibility of using electronic tongues as systems for the easy, rapid and effective sensorial assessment of vegetable milks.

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TABLE CAPTIONS

Table 1: List of the vegetable milks tested during the study and their abbreviations.

Table 2: List of sensorial attributes (ordered alphabetically) and their abbreviations.

Table 3. 3a: Mean values and standard deviations obtained in the sensorial tests for each parameter and sample on a scale of 1-10. **3b**: Medians of the sensorial tests. The values with the same letter in superscript indicate homogeneous groups for a certain attribute

Table 4: Adjusting parameters (R^2 and RMSEP) from the PLS prediction models for the sensorial scores of vegetable milks. **4a**: training set. **4b**: validation set

FIGURE CAPTIONS

Figure 1: The applied potentials (solid line) and the current response (dashed line) of waveform applied to the TNA sample when a silver electrode was used.

Figure 2: Principal component analysis (PCA) of the marks obtained from the sensorial analysis; A) Scores plot, B) Loading plot

Figure 3: Principal component analysis (PCA) score plot of the marks obtained from the current measured with the electronic tongue.

Figure 4: Hierarchical cluster analysis of the eight samples and three replicates per sample using Ward's method.

Figure 5: Experimental *versus* predicted values using a PLS statistical model (dashed lines). The solid line represents ideal behaviour; A) BODY, B) HOMCOL and C) GRANWG.

Table 1

Raw material	Origin	Abbreviation	Number of sensorial measurements
Soya	Commercial	SOYA	48
Oat	Commercial	OAT	56
Rice	Commercial	RICE	55
Almond	Commercial	ALMOND	57
Tiger nut	Commercial	TNA	50
Tiger nut	Commercial	TNB	47
Tiger nut	Artisanal-Valencia	VLC	45
Tiger nut	Artisanal-Burkina Faso	BFA	43

Table 2

Sensorial attribute	Range	Abbreviation
Aroma of tiger nut	Slightly appreciable / most appreciable	AROMA
Body	Light-bodied / full-bodied	BODY
Colour	Light beige / Dark or deep beige	COLOUR
Film in the wall of glass	Slightly appreciable / most appreciable	FILMWG
Granularity in the wall of glass	Slightly grainy / very grainy	GRANWG
Homogeneity of colour	Slightly homogeneous / very homogeneous	HOMCOL
Rancid flavour / taste of old	Slightly appreciable / most appreciable	OLDFLAV
Residual flavour	Slightly appreciable / most appreciable	RESFLAV
Roughness in mouth	Slightly rough / very rough	ROUGH
Strange aromas	Slightly appreciable / most appreciable	STRANGE
Sweetness	Slightly sweet / very sweet	SWEET
Typical flavour of tiger nut milk	Slightly appreciable / most appreciable	TYPFLAV

Table 3

Table 3a

Sensorial attribute	SOYA	OAT	RICE	ALMOND	TNA	TNB	VLC	BFA
AROMA	2.4±0.9	4.6±1.7	2.6±1.5	3.1±1.5	5.5±1.7	4.5±1.8	5.4±1.9	5.4±1.7
BODY	3.7±1.5	2.6±1.4	2.1±1.1	4.0±1.1	4.9±2.0	3.7±1.6	5.2±1.9	6.0±1.9
COLOUR	7.8±1.2	7.9±1.1	1.2±0.8	1.3±1.1	4.8±1.5	3.3±1.6	3.9±1.8	6.5±1.7
FILMWG	4.7±1.3	3.5±1.7	4.2±1.7	5.0±1.4	4.9±1.9	5.5±1.5	6.5±1.8	7.3±1.4
GRANWG	3.3±1.3	3.3±1.7	1.8±0.8	4.6±1.5	4.7±1.9	4.3±1.8	4.6±1.6	7.2±1.4
HOMCOL	7.9±1.0	7.2±1.4	8.8±0.5	8.3±0.7	6.8±1.3	6.8±1.2	6.9±1.6	5.9±1.7
OLDFLAV	3.2±1.2	3.5±1.7	3.8±1.7	2.4±1.1	1.9±1.3	1.1±0.5	2.5±1.6	7.0±1.9
RESFLAV	5.4±1.6	5.4±1.5	4.1±1.3	3.8±0.8	5.2±1.7	3.8±1.5	5.2±1.9	6.8±1.9
ROUGH	4.5±1.6	2.5±0.8	3.1±1.3	4.1±1.3	3.2±1.8	2.7±1.3	4.0±2.0	5.8±1.8
STRANGE	3.3±1.5	5.5±0.6	5.0±1.3	4.5±1.4	1.4±0.8	1.6±0.7	3.0±2.0	7.1±1.6
SWEET	1.3±0.9	3.4±1.6	3.2±1.5	7.7±0.9	6.1±1.7	5.4±1.6	6.4±1.7	3.3±1.7
TYPFLAV	1.6±1.1	2.3±1.5	2.9±1.9	4.1±1.4	5.6±2.0	5.6±1.3	7.3±1.6	4.3±1.9

Table 3b

Sensorial attribute	SOYA	OAT	RICE	ALMOND	TNA	TNB	VLC	BFA
AROMA	2.4^{b}	4.4^{c}	2.1^{b}	3.1^{a}	5.8^{d}	4.5^{cd}	5.7^{d}	5.5^{d}
BODY	3.5^{ace}	2.8^{c}	1.8^{b}	3.9^{a}	5.0^{ef}	3.9^{ae}	5.5^{df}	6.2^{d}
COLOUR	7.9^{b}	8.1^{b}	1.2^{a}	0.7^{a}	4.7^{e}	3.2^{d}	3.8^{de}	6.8^{c}
FILMWG	4.9^{a}	3.6^{b}	4.6^{ab}	5.1^{a}	5.3^{a}	5.6^{a}	6.6^{c}	7.5^{c}
GRANWG	3.4^{ce}	3.3^{c}	2.0^{b}	4.5^{a}	5.2^{a}	4.3^{ae}	4.6^{a}	7.4^{d}
HOMCOL	8.1^{a}	6.9^{cd}	8.9^{b}	8.5^{a}	7.0^{d}	6.8^{cd}	7.1^{d}	5.9^{c}
OLDFLAV	3.3^{b}	3.8^{b}	3.9^{b}	2.3^{a}	1.9^{a}	1.1^{a}	2.4^{a}	7.2^{c}
RESFLAV	5.5^{b}	5.2^{b}	4.2^{a}	3.7^{a}	5.2^{b}	3.7^{a}	5.6^{b}	7.0^{c}
ROUGH	4.4^{a}	2.4^{b}	3.0^{bc}	4.0^{a}	3.1^{bc}	2.5^{b}	3.8^{ac}	5.6^{d}
STRANGE	2.8^{e}	5.5^{b}	5.1^{ab}	4.5^{a}	1.3^{d}	1.5^{d}	2.7^{e}	7.0^{c}
SWEET	1.4^{e}	3.7^{b}	3.1^{b}	7.9^{a}	6.4^{d}	5.4^{c}	6.6^{d}	3.4^{b}
TYPFLAV	1.6^{b}	2.0^{b}	2.3^{b}	4.3^{a}	5.7^{cd}	5.7^{d}	7.7^{e}	4.5^{ac}

Table 4

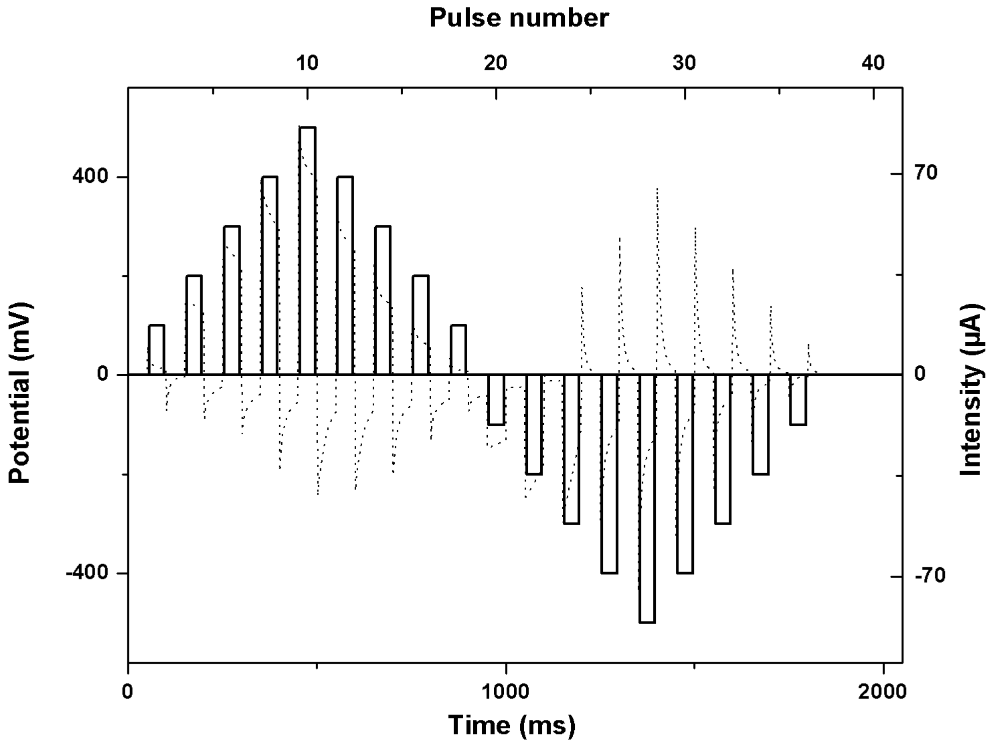
Table 4a. Training Set

Sensorial attribute	LV model	R^2	RMSE	a	b	Value range
Aroma of tiger nut	5	0.979	0.4268	0.9791	0.0884	1-10
Body	5	0.982	0.0966	0.9824	0.0711	1-10
Colour	5	0.973	0.6375	0.9729	0.1228	1-10
Film in the wall of glass	4	0.976	0.1146	0.9756	0.1259	1-10
Granularity in the wall of glass	6	0.985	0.1073	0.9853	0.0619	1-10
Homogeneity of colour	5	0.984	0.0452	0.9841	0.1129	1-10
Rancid flavour / taste of old	5	0.977	0.2180	0.9771	0.0744	1-10
Residual flavour	5	0.966	0.1126	0.9662	0.1690	1-10
Roughness in mouth	5	0.975	0.0976	0.9746	0.960	1-10
Strange aromas	5	0.973	0.3057	0.9727	0.1049	1-10
Sweetness	5	0.976	0.3462	0.9758	0.1108	1-10
Typical flavour of tiger nut milk	5	0.989	0.1375	0.9890	0.0462	1-10

Table 4b. Validation Set

Sensorial attribute	LV model	R^2	RMSE	a	b	Value range
Aroma of tiger nut	5	0.860	0.1029	0.8822	0.4041	1-10
Body	5	0.957	0.2852	0.8838	0.5877	1-10
Colour	5	0.806	1.1455	0.7567	0.7129	1-10
Film in the wall of glass	4	0.841	0.4435	0.9123	0.5042	1-10
Granularity in the wall of glass	6	0.940	0.3980	1.0793	-0.2336	1-10
Homogeneity of colour	5	0.975	0.1635	1.0306	-0.1375	1-10
Rancid flavour / taste of old	5	0.549	1.2580	0.8860	0.4965	1-10
Residual flavour	5	0.781	0.4424	0.8939	0.5338	1-10
Roughness in mouth	5	0.853	0.4409	1.0473	-0.0746	1-10
Strange aromas	5	0.463	1.3132	0.6548	1.3826	1-10
Sweetness	5	0.607	1.1915	0.5677	2.0427	1-10
Typical flavour of tiger nut milk	5	0.710	1.0907	0.4563	2.3014	1-10

Figure 1



Pulse number
10
20
30
40
400
0
-400
70
0
-70
Potential (mV)
Intensity (μA)
0
1000
2000
Time (ms)

Figure 2

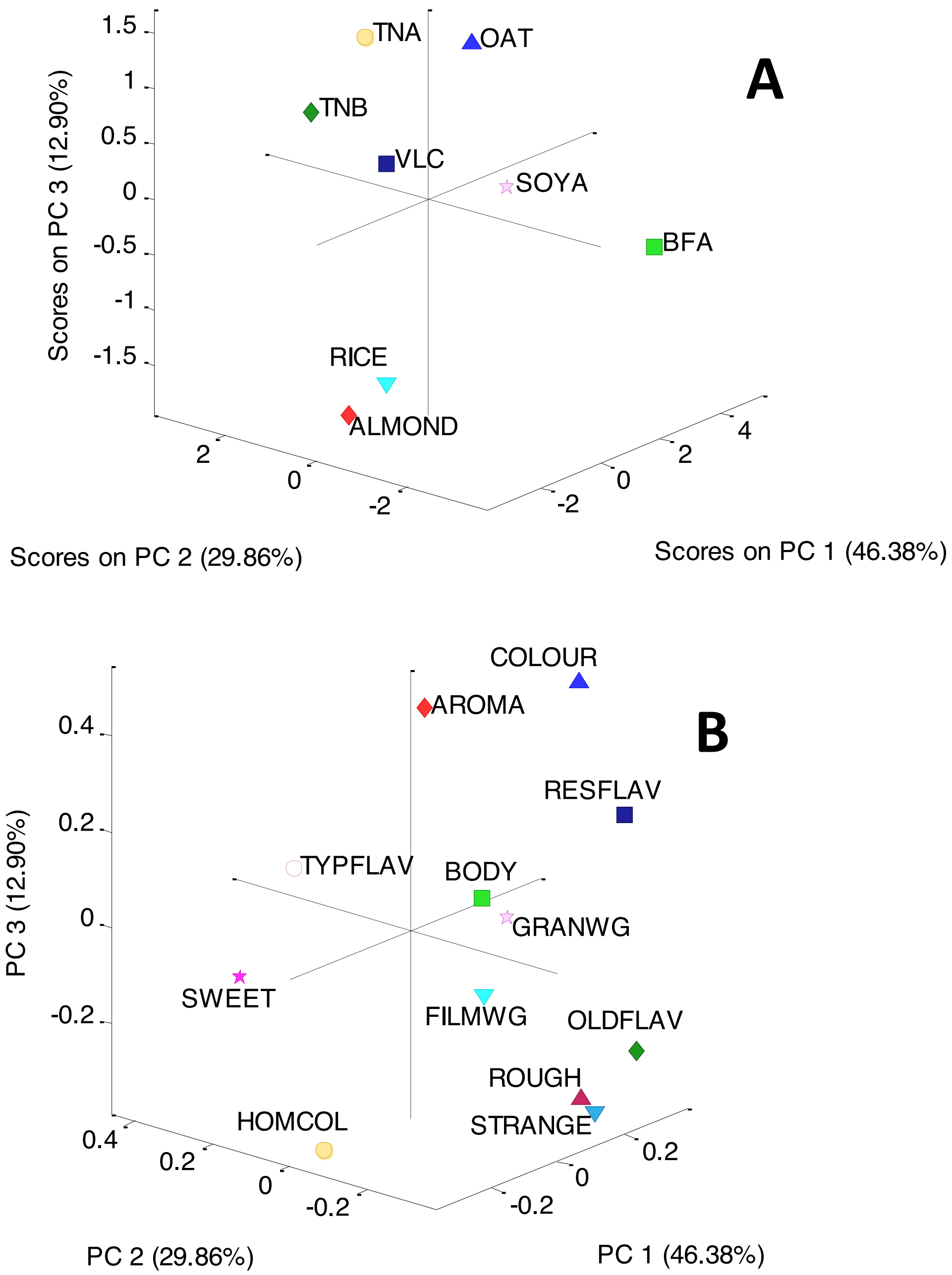
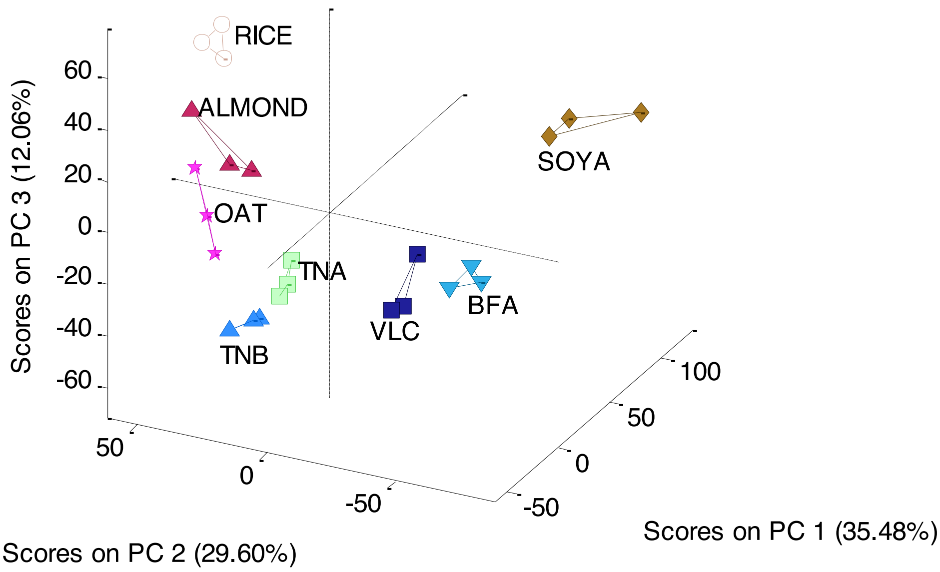

A
Scores on PC 3 (12.90%)
1.5
1
0.5
0
-0.5
-1
-1.5
TNA
OAT
TNB
VLC
SOYA
BFA
RICE
ALMOND
2
0
-2
-2
0
2
4
Scores on PC 2 (29.86%)
Scores on PC 1 (46.38%)
B
PC 3 (12.90%)
0.4
0.2
0
-0.2
COLOUR
AROMA
RESFLAV
TYPFLAV
BODY
GRANWG
SWEET
FILMWG
OLDFLAV
ROUGH
STRANGE
HOMCOL
0.4
0.2
0
-0.2
-0.2
0
0.2
PC 2 (29.86%)
PC 1 (46.38%)

Figure 3



RICE
ALMOND
OAT
SOYA
TNA
TNB
VLC
BFA
60
40
20
0
-20
-40
-60
Scores on PC 3 (12.06%)
50
0
-50
Scores on PC 2 (29.60%)
100
50
0
-50
Scores on PC 1 (35.48%)

Figure 4

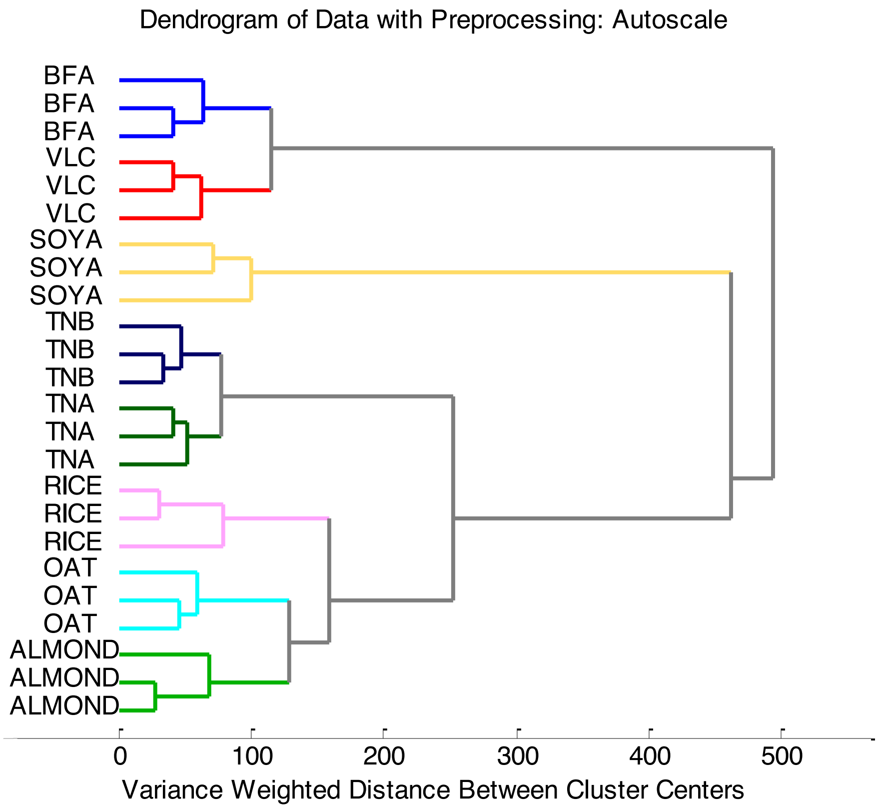
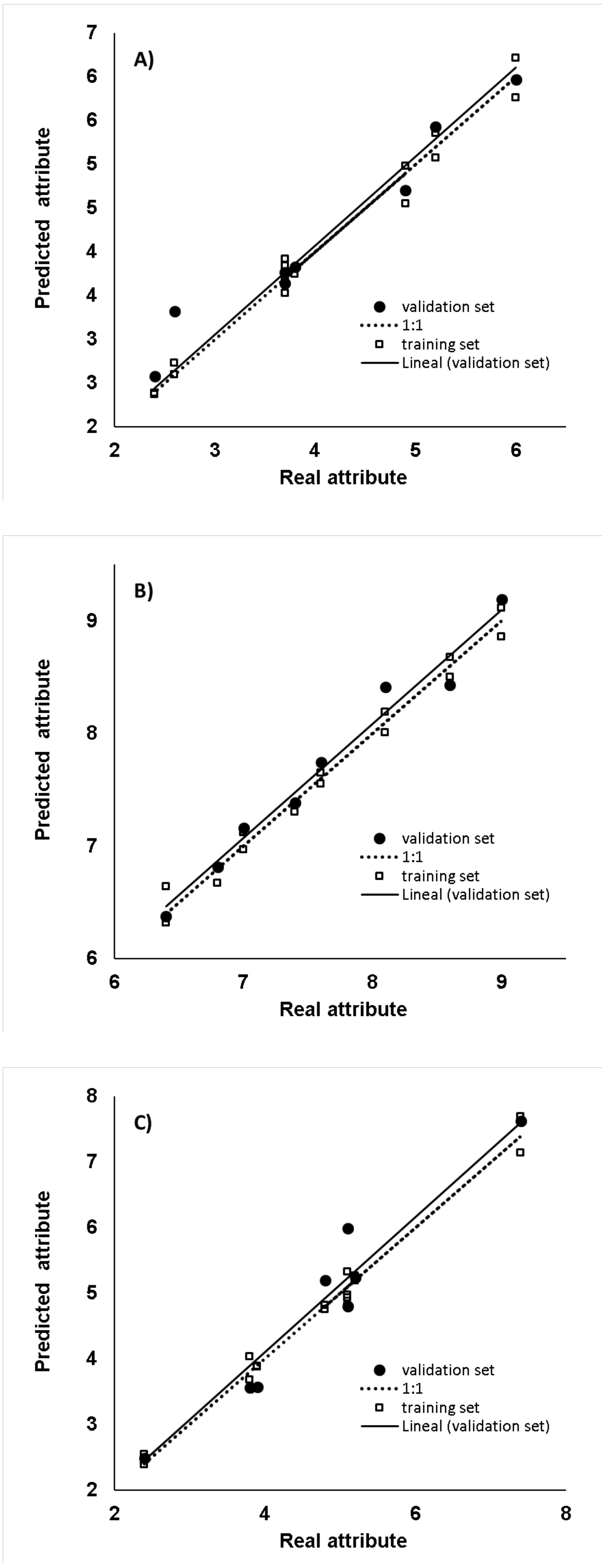

Dendrogram of Data with Preprocessing: Autoscale
BFA
BFA
BFA
VLC
VLC
VLC
SOYA
SOYA
SOYA
TNB
TNB
TNB
TNA
TNA
TNA
RICE
RICE
RICE
OAT
OAT
OAT
ALMOND
ALMOND
ALMOND
0
100
200
300
400
500
Variance Weighted Distance Between Cluster Centers

Figure 5


A)
B)
C)
validation set
1:1
training set
Lineal (validation set)
Predicted attribute
Real attribute