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Analysis of tomato taste using two types of electronic tongues

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Abstract

In this study the potential of two types of electronic tongues as rapid techniques to analyze taste is evaluated. The first electronic tongue was developed at the University of Saint-Petersburg and comprises of 18 potentiometric sensors. The second electronic tongue was the ASTREE electronic tongue developed by Alpha M.O.S. (Toulouse, France) which consists of a set of seven sensors which are commercially available. Six Belgian tomato cultivars were classified according to similarity in taste profile using both multisensor systems. The tomato cultivars were selected based on their difference in sweetness and sourness as perceived by trained sensory panels. The concentration of sugars (glucose and fructose), organic acids (citric acid, malic acid and glutamic acid) and minerals (Na and K) were also determined with reference techniques. Multivariate statistical data analysis techniques as principal components analysis (PCA), canonical discriminant analysis (CDA) and partial least squares regression (PLS) were used to classify tomato cultivars according to similarity in taste profile and to quantitatively relate the taste compounds to the sensory panel scores. Both electronic tongues were very well suited to classify tomato cultivars based on their taste profile. To quantify individual sugars, acids and minerals in a complex mixture the system which was developed at the University of Saint-Petersburg was highly appropriate, but this system could not predict general sweetness and umami taste as evaluated by the sensory panel. The ASTREE electronic tongue on the other hand was suitable to quantify glutamic acid and Na, but the sensor readings were poorly correlated to the sweetness, sourness, saltiness and umami in tomato as tasted by the sensory panel.

Keywords: Electronic tongue; Tomato; Taste sensory evaluation; Multivariate data analysis

1. Introduction

Sensory and instrumental techniques are traditionally used to determine the taste of food products. Trained and consumer panels give by far the most realistic image of the taste of a product as experienced by human. Sensory analysis however has some serious drawbacks, namely the correctness of training, standardization of measurements, reproducibility, high cost and taste saturation of the panelist [1]. High-pressure liquid chromatography (HPLC), gas chromatography (GC) and other instrumental techniques determine the chemical composition of a sample and could be used to describe the taste of a food product. These traditionally used instrumental techniques show some drawbacks too. They require laborious and time-consuming sample preparation and skilled people to operate the equipment [2].

In food research there is a need for objective high-throughput taste profiling to complement sensory panels. Electronic tongues have proven to be a good alternative for traditional chromatographic techniques in the analysis of food. Over the past years different types of electronic tongues have been developed by several institutes and universities all over the world [3]. The basic idea behind electronic tongue technology is the application of an array of non-specific chemical sensors with a high cross-sensitivity, i.e. a wide selectivity towards several components in a sample. Different electronic tongues have proven to be successful in discrimination and classification, quality evaluation and control, process monitoring and quantitative analysis of foodstuff and beverages. The main advantages of electronic tongues are the low cost, easy-to-handle measurement set-up and speed of the measurements [4,5]. The four best known electronic

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tongues have been developed by Toko in Japan [6,7], Winquist et al. at the Swedish Sensor Centre S-SENCE [8,9], the University of Saint-Petersburg in Russia [2,10–13] and Alpha M.O.S. in France [14,15].

In this study the electronic tongue developed at the University of Saint-Petersburg and the one developed by Alpha M.O.S. (Toulouse, France) are evaluated for applications in horticulture. The electronic tongue from Saint-Petersburg University is based on specially designed non-specific, weakly selective potentiometric chemical sensors with an enhanced cross-sensitivity to as many components in solution as possible [3,11]. These non-specific sensors are comprised into sensor arrays producing multidimensional response, which contains information on several components or groups of components in a complex sample [2,3]. The electronic tongue is capable of both qualitative recognition and quantitative determination of taste. It has been applied in food research for the analysis of taste compounds in tomato [2] and apple [10], analysis of Italian wine [5], analysis of beverages [11,13], quantitative analysis of mineral water and wine [12], recognition of liquid and flesh food [16] and analysis of Korean green tea [17].

During the nineties Alpha M.O.S. successfully developed electronic noses and tongues for the measurement of aroma and taste. The “ASTREE” liquid and taste analyzer is made out of seven liquid sensors, which are available in two different sets, with a cross-selectivity to dissolved organic compounds in liquids [18]. The ASTREE, in combination with the electronic nose, is able to classify food and beverages [18], determine bitterness in coffee [18] and predict sensory characteristics of apple juice [19]. Since it is a commercial product, no details are available on the sensor array.

The objective of this experiment is to evaluate the potential of both electronic tongues for fast qualitative and quantitative determination of taste in Belgian tomato cultivars. Hereto, first, the information content of the electronic tongues will be compared to that of a high-throughput bioanalytical method and atomic absorption spectrometry. Second, the ability of the electronic tongues to predict the chemical composition and taste of the tomatoes will be investigated using multivariate statistical techniques.

2. Experimental

2.1. Samples

Six tomato cultivars (*Lycopersicon esculentum* Mill.) were selected based on their difference in taste, which is mainly defined by the difference in sweetness and sourness (Table 1) to assure a broad range in acid and sugar content. The selected cultivars are: Admiro, Macarena, Sunstream, Amoroso, Tricia and Clotilde. The fruits were obtained at the fruit and vegetable Auction of Mechelen (Belgium) and the Auction of Hoogstraten (Belgium). All tomatoes were picked at ripeness stage 6 (breaker class) [20]. The fruits were stored during 1 day at ambient atmosphere, 18 °C and 80% relative humidity. The day after purchase the tomatoes were juiced and the juice of the different tomatoes was mixed all together in a bucket (10 l). The juice was then divided over several falcon tubes and frozen in liquid nitrogen. The samples were stored at −80 °C until measurement.

Table 1
Sweetness and sourness of the six Belgian tomato cultivars

	Sweet	Sour
Admiro	0	0
Macarena	−	+
Sunstream	+	−
Amoroso	+	+
Tricia	−	−
Clotilde	0	0

+: high; 0: intermediate; −: low.

2.2. Electronic tongue Saint-Petersburg University

The electronic tongue developed at Saint-Petersburg University consists of a sensor array of 18 potentiometric chemical sensors. The array contains anionic sensors and cationic sensors, selected for their sensitivity to organic acids and minerals, and a pH sensor. Sensor potential values are measured versus a conventional Ag/AgCl reference electrode with a precision of 0.1 V. When the sensors are put in the tomato juice, within 3 min a potential over the electrode membrane reaches an equilibrium value which is related to the chemical composition of the sample. The 18 potential values are recorded in PC data files. The electronic tongue measurements were performed on juices of the tomato samples without special sample preparation. Ten milliliter of tomato juice was simply diluted with 50 ml of distilled water to reach a total volume which allowed all sensors to be immersed in the sample. In between the measurements the sensors were rinsed using distilled water for 7 min until stable sensor readings were recorded. After 1 and 4 min the distilled water was renewed. Sixty tomato samples were analyzed using this technique.

2.3. ASTREE electronic tongue

The ASTREE electronic tongue developed by Alpha M.O.S. is composed out of seven liquid sensors. The commercially available set #1 (sensors ZZ, BA, BB, CA, GA, HA and JB) was chosen for this particular experiment. The sensors show selectivity to sugars, acids and minerals. Measurement time was set equal to the measurement time of the electronic tongue developed at the University of Saint-Petersburg, i.e. 3 min. The measurements were performed on 90 ml of centrifuged tomato juice. This means a starting volume of 150 ml of tomato juice was required for the analysis. Samples were centrifuged using a KR 22i centrifuge (Jouan, Saint-Herblain, Cedex, France) at 14,000 rpm during 5 min. In between measurements the sensors were rinsed using distilled water during 20 s. The sensors did not always reach their baseline potential after this short cleaning period. Because of this a large drift is present in the measurement data. Data analysis was performed on absolute data, as advised by the Alpha M.O.S. company. Seventy-two tomato samples were analyzed using this technique.

2.4. Reference techniques: EHT and AAS

A high-throughput bioanalytical method (EHT) was used as a reference technique to evaluate sugar and acid content of the tomato samples. An automated liquid handling system (Multiprobe® II Plus, PerkinElmer, Boston, USA) with four channels was programmed to dispense all the reagents in the wells of the microtitre plates. Ninety-six-well (NUNC, Roskilde, Denmark) and 384-well (Corning, New York, USA) flat-bottomed non-treated polystyrene microtitre plates were used. The absorbances at the specified wavelengths were read with a Multiskan Spectrum (Thermo Electron Corporation, Waltham, USA). The enzymatic assays for the analysis of glucose, fructose, citric acid, malic acid and glutamic acid were purchased from R-Biopharm (Darmstadt, Germany). The assays are based on an increase/decrease in absorbance at specific wavelengths caused by a change in NAD(P)H (340 nm). The absorbance of the chromogenic molecules is measured before and after the addition of the substrate specific enzyme and is corrected for the delta absorbance of the blank values. The tomato samples were filtered using a 0.45 μm pore filter (Alltech Associates Inc., Deerfield, USA) preceding the analysis. All samples were analyzed in double together with a calibration curve, consisting of four points with three repetitions per concentration, on the same microtitre plate. All compounds were purchased at Sigma–Aldrich (Steinheim, Germany). Since the concentrations of the acids and sugars in the samples were too high to be analyzed directly, dilution with distilled water was necessary to obtain concentrations that were in the linear range of the calibration curve. For a detailed description of this technology the reader is referred to [21]. Four repetitions of each cultivar were analyzed using this fast reference technique.

For the analysis of minerals atomic absorption spectroscopy (AAS) was applied as a reference technique. The concentrations of Na and K, which have an influence on the saltiness of the tomato samples, were determined using a flame atomic absorption spectrometer type Solaar 969 A (Thermo Elemental, Cambridge, UK). The tomato samples were filtered using a 0.45 μm pore filter. Five samples per cultivar were analyzed using this technique.

2.5. Sensory panel evaluation

The sensory panel analysis of the tomato taste was conducted in the Sensory Laboratory at the Vegetable Research Centre in Kruishoutem, Belgium. The sensory laboratory houses a test room with 14 individual booths constructed according to the ISO 8589 norm [22]. A panel of nine persons was trained over a 6-week period to evaluate sensory attributes of tomatoes focusing on taste. A list of the sensory attributes and references used is given in Table 2.

Table 2
Sensory attributes as determined by the trained taste panel

Attribute	Reference compound
Sweetness	Fructose
Sourness	Citric acid
Saltiness	NaCl (kitchen salt)
Umami	Mono-Na-glutamate (taste additive)

The experiment was conducted in four sessions and all six cultivars were evaluated in each session. The panellists were asked to score the taste attributes of the tomato juice contained in closed cups. The evaluations were performed at room temperature (18–20 °C) under red light. Samples were presented in a comparative way using a Latin square design to avoid effects of order and first position. For each product, the assessors scored intensities for the perceived attributes on unstructured 10 cm line scales anchored by the terms ‘weak’ (0) and ‘strong’ (10). Between samples panellists could rinse their mouth with water and eat white salt-free bread.

2.6. Statistical analysis

The results of the reference techniques were analyzed using analysis of variance (ANOVA). A Tukey test was performed to find significant differences between the cultivars in the content of sugars and acids as measured by EHT and minerals as measured by AAS.

The multidimensional signals of both electronic tongues required some data pretreatment before statistical analysis could be performed. The electronic tongue developed at the University of Saint-Petersburg is comprised of 18 potentiometric sensors of which some were sensitive to drift during the duration of the experiment. The drifting sensors were deleted from the sensor array based on the sensor stability and sensitivity. The canonical variable (CV)-values of all sensors of both electronic tongue systems are shown in Table 3. Sensors with a CV-value of more than 10 were considered as unstable during the experiment. Fourteen sensors of the electronic tongue developed at Saint-Petersburg University were retained for further data analysis. One of the sensors deleted from the array is the pH sensor. An explanation for its instability can be found in the material it is made off. Since the sensor contains oxide glass it can show some instability in samples containing organic material. Only a few sensors of the ASTREE electronic tongue were stable during the experiment and sensitive towards the tomato samples. Most sensors however were very sensitive to drift, most probably due to the cleaning method prescribed by the Alpha M.O.S. company. The most drifting sensor JB, with a CV-value higher than 10, was deleted from the sensor array during data analysis.

Multivariate data analysis was applied for both qualitative and quantitative analysis [23]. Unsupervised as well as supervised statistical techniques can be used to analyze the ability of the two electronic tongue technologies to discriminate qualitatively between tomato cultivars. Principal component analysis (PCA), an unsupervised method, was used for data visualization and the detection of groups in the data structure. The analysis was performed on the correlation matrices, outliers were deleted from the analysis. As a supervised method, canonical discriminant analysis (CDA) was used to group the cultivars. The results of the CDA and PCA performed on the electronic tongue data were compared to those of the reference techniques. Partial least squares analysis (PLS), using cross-validation, was performed

Table 3
CV-values of all sensors in the electronic tongue developed at Saint-Petersburg University (a) and the ASTREE electronic tongue (b)

Sensor	CV-value
(a) Saint-Petersburg University	
Sensor 1	2.53
Sensor 2	4.02
Sensor 3	5.18
Sensor 4	7.25
Sensor 5	3.05
Sensor 6	2.37
Sensor 7	2.07
Sensor 8	3.48
Sensor 9	4.43
Sensor 10	3.89
Sensor 11	8.02
Sensor 12	167.84
Sensor 13	20.05
Sensor 14	14.21
Sensor 15	3.15
Sensor 16	2.52
Sensor 17	2.55
pH sensor	175.13
(b) ASTREE electronic tongue	
Sensor ZZ	3.29
Sensor BA	3.22
Sensor BB	1.18
Sensor CA	2.30
Sensor GA	3.64
Sensor HA	3.65
Sensor JB	34.97

to study the predictive capacity of both electronic tongues for individual compounds. The concentration of sugars, acids and minerals and taste attributes scored by the sensory panels were predicted using PLS. The results of the EHT and AAS measurements were taken as references for the assessment of individual chemical compounds and the panel scores were used for the prediction of taste. For data analysis two different computer software programs were used: the Unscrambler version 9.1.2 (CAMO Technologies Inc., Woodbridge, USA) and SAS version 9.1 (SAS Institute Inc., Cary, USA).

3. Results and discussion

3.1. Exploration of the data

The data measured by the reference techniques, EHT and AAS, were analyzed with ANOVA. Significant differences between cultivars based on individual sugars, acids and minerals are shown in Table 4. Amoroso, which is a cherry cluster tomato, has high concentrations of both sugars, citric acid, glutamic acid and both measured minerals and a low concentration of malic acid. Due to its chemical content this is a very tasty tomato (Table 1). Sunstream, another cocktail cluster tomato, also shows high concentrations of both sugars, but significantly lower than Amoroso. Tricia has low concentrations of all compounds.

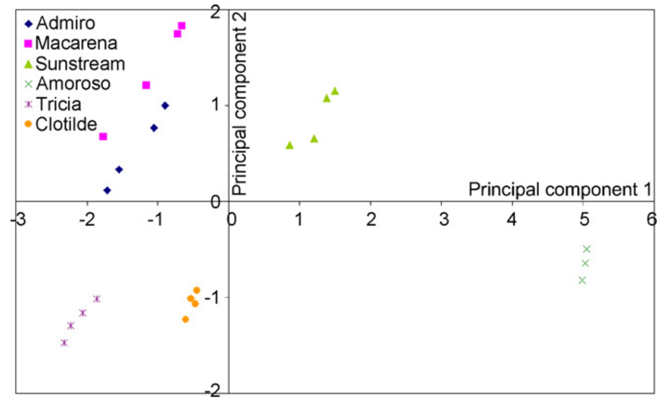

Fig. 1. PCA score plot of the results of EHT and AAS.

3.2. Classification of tomato cultivars: comparison of electronic tongues to reference techniques

Fig. 1 shows the results of the PCA on the data of both reference techniques, EHT and AAS. The six tomato cultivars can be separated based on their sugar, acid and mineral content. Ninety percent of the variance is explained by the first two principal components (PC). Despite the fact that Admiro and Macarena have a very different chemical composition, they are close to each other in the score plot. Amoroso, the cherry cluster tomato, is clearly separated from the other cultivars along the axis of the first PC. According to the correlation loading plot the main compounds that cause this separation are glucose and fructose. Table 4 also shows that the sugar content of Amoroso is significantly higher than that of the other cultivars.

A PCA was performed on the electronic tongue developed at the University of Saint-Petersburg. The sensors with low stability were deleted from the data set, so that 14 sensors were retained for statistical analysis (Table 3). In the PCA Amoroso can again be separated from the other cultivars along the axis

Table 4
ANOVA results (average ± standard deviation) of EHT and AAS measurements on six tomato cultivars (glucose, fructose, citric acid, malic acid and glutamic acid in g/l; Na and K in mg/l)

	Glucose	Fructose	Citric acid	Malic acid	Glutamic acid	Na	K
Admiro	11.2 ± 0.3 e	11.3 ± 0.3 e	4.8 ± 0.5 bc	0.7 ± 0.6E−2 b	1.0 ± 0.3E−1 d	9.2 ± 0.2 c	1827.6 ± 180.0 bc
Macarena	15.6 ± 0.2 c	14.4 ± 0.2 c	4.3 ± 0.5 cd	0.9 ± 1.7E−2 a	0.6 ± 0.2E−1 e	7.4 ± 0.4 c	1911.2 ± 338.8 bc
Sunstream	17.7 ± 0.4 b	17.4 ± 0.3 b	5.4 ± 0.4 ab	0.5 ± 1.5E−2 d	1.5 ± 0.2E−1 b	7.9 ± 0.6 c	2225.3 ± 312.8 b
Amoroso	23.7 ± 0.3 a	23.5 ± 0.5 a	5.8 ± 0.3 a	0.3 ± 0.5E−2 e	2.8 ± 0.8E−1 a	82.9 ± 4.1 a	2655.6 ± 86.6 a
Tricia	10.0 ± 0.1 f	10.8 ± 0.1 e	2.9 ± 0.4 e	0.5 ± 1.1E−2 d	0.9 ± 0.3E−1 d	8.8 ± 0.6 c	1559.8 ± 122.7 c
Clotilde	13.3 ± 0.2 d	13.4 ± 0.2 d	3.7 ± 0.3 de	0.5 ± 0.7E−2 c	1.1 ± 0.1E−1 c	46.0 ± 3.4 b	1772.5 ± 44.1 c

Significant differences ($\alpha = 0.05$) between cultivars are given by different letters; they should be read per chemical compound.

of the first PC. The cationic sensors are responsible for this separation. They show a high correlation with the first PC. Macarena and Tricia are also slightly separated from the other cultivars. If Amoroso is excluded from the analysis, they clearly are classified together and separated from Admiro, Sunstream and Clotilde. The separation of Amoroso, Macarena and Tricia is probably caused by the difference in the content of both sugars and minerals (Table 3).

The PCA performed on the results of the ASTREE electronic tongue using all seven sensors show that 99% of the variability is explained by the first two PCs. The samples of all cultivars are spread along the axis of the first PC. Looking at the correlation loadings it seems that sensor JB is mainly responsible for this spreading within the cultivars. Despite the drift along the first PC, Amoroso and Clotilde are separated from the other four cultivars along the axis of the second PC. After excluding sensor JB from the dataset, Amoroso and Clotilde are again separated from the other cultivars. This time the separation mainly occurs along the axis of the first PC. The clustering of Amoroso and Clotilde cannot be explained by their chemical composition, since both cultivars have very different concentrations and proportions of sugars, acids and minerals (Table 4). In the cluster of the other four cultivars a trend can be seen. Admiro is slightly separated from Macarena, Sunstream and Tricia.

In Fig. 2a the results of the CDA performed on the data of the reference measurements are shown. Separation between cultivars is clearly achieved using EHT and AAS. Within-cultivar variability is small compared to between-cultivar variability. From the total-sample standardized canonical coefficients can be seen that the separation along the first canonical variable is based on differences in glutamic acid and Na concentrations. Amoroso, which is clearly separated from the other cultivars, contains a significantly higher concentration of both compounds. Separation along the second CV is caused by Na, glucose and fructose. Admiro, Tricia and Clotilde have significantly lower concentrations of both glucose and fructose compared to Macarena and Sunstream (Table 4).

The results of the CDA performed on the data of the electronic tongue developed at the University of Saint-Petersburg are shown in Fig. 2b. Using CDA is seems possible to classify tomato cultivars. Comparing these results to the measurements of the reference method (Table 4) and the taste of the tomatoes (Table 1), some correlations can be seen. The first CV is clearly negatively correlated with the Na content of the samples. Amoroso and Clotilde contain higher concentrations of Na than the other four cultivars. There also appears to be a correlation between the classification along the first CV and the overall sweet taste. Amoroso and Sunstream are positioned opposite from Macarena and Tricia, which have a less sweet taste. The separation of the six cultivars is also clear along the second CV. This second axis seems to be correlated with the overall sour taste. Macarena, Amoroso and Clotilde have a more sour taste than the other three cultivars. There are obvious correlations too between the sensors of the electronic tongue developed at the University of Saint-Petersburg and the reference techniques. Fig. 2a and b shows the same results after translation over the two axes. The variability within the cultivars is comparable for both this multisensor system and the reference techniques.

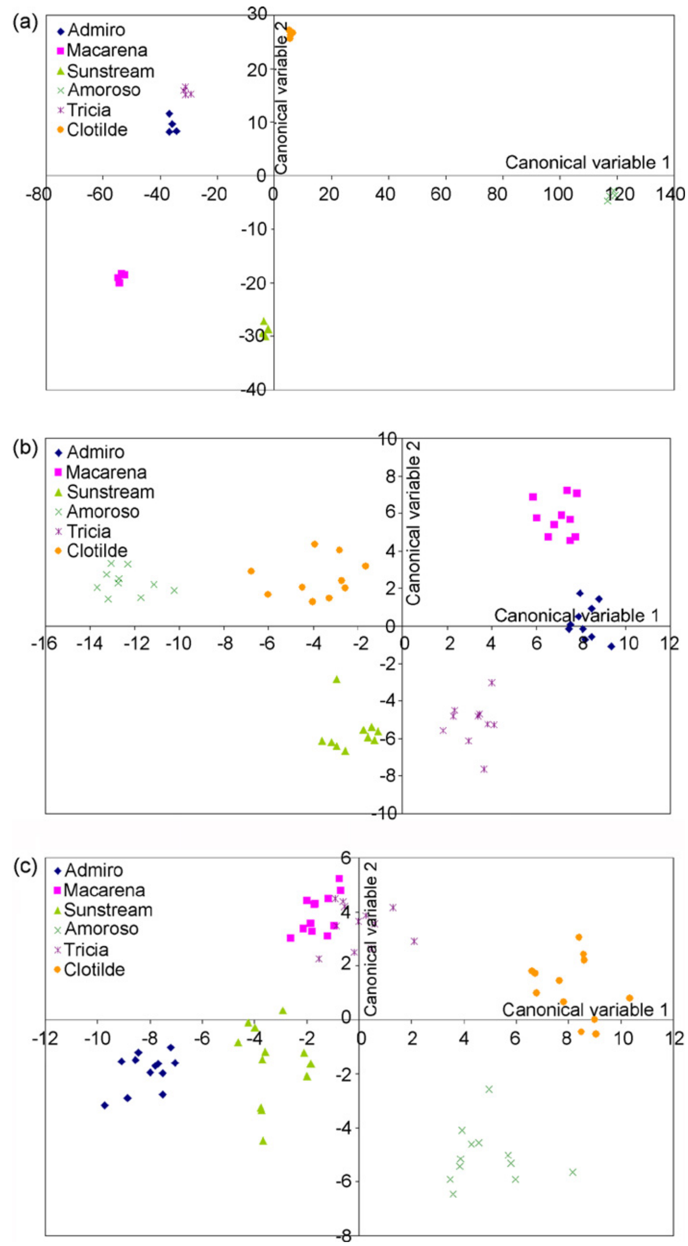

Fig. 2. CDA plot of the results of EHT and AAS (a), the electronic tongue developed at the University of Saint-Petersburg (b) and the ASTREE electronic tongue without sensor JB (c).

A CDA was also performed on the data form the ASTREE electronic tongue (Fig. 2c). All sensors, except for the drift-causing sensor JB, were included in the analysis. Again a good discrimination between the cultivars can be seen. Macarena and Tricia however show some overlap. According to the total-sample standardized canonical coefficients, sensors BB and CA are responsible for both the separation along the axis of CV1 and CV2. There does not seem to be any correlation with the results of the reference techniques (Table 4) and the taste (Table 1) of the analyzed tomatoes. The within-cultivar variability using this electronic tongue system however is comparable to that of the reference techniques.

Table 5
PLS calibration models (cross-validation) to predict individual compounds built on the results of the electronic tongue developed at Saint-Petersburg University (logarithm of concentration) (a) and the ASTREE electronic tongue (concentration) (b)

	Slope	Offset	Correlation	RMSEC/RMSECV
(a) Saint-Petersburg University (logarithm of concentration)				
Glucose				
Calibration	0.96	0.04	0.98	0.02
Validation	0.93	0.08	0.95	0.04
Fructose				
Calibration	0.98	0.03	0.99	0.02
Validation	0.95	0.05	0.96	0.03
Citric acid				
Calibration	0.92	0.05	0.96	0.03
Validation	0.84	0.10	0.87	0.05
Malic acid				
Calibration	0.97	−0.01	0.98	0.03
Validation	0.94	−0.02	0.96	0.05
Glutamic acid				
Calibration	0.96	0.03E−1	0.98	0.04
Validation	0.94	0.02E−1	0.95	0.06
Na				
Calibration	0.99	0.01	0.99	0.04
Validation	0.92	0.10	0.97	0.10
K				
Calibration	0.95	0.16	0.97	0.02
Validation	0.91	0.30	0.91	0.04
(b) ASTREE electronic tongue (concentration)				
Glucose				
Calibration	0.52	7.17	0.72	2.98
Validation	0.36	9.73	0.49	3.90
Fructose				
Calibration	0.61	5.81	0.78	2.53
Validation	0.47	8.05	0.56	3.52
Citric acid				
Calibration	0.65	1.58	0.80	0.64
Validation	0.54	2.15	0.62	0.89
Malic acid				
Calibration	0.70	0.17	0.84	0.10
Validation	0.58	0.25	0.72	0.12
Glutamic acid				
Calibration	0.81	0.24	0.90	0.29
Validation	0.74	0.33	0.80	0.41
Na				
Calibration	0.87	3.12	0.94	9.53
Validation	0.80	5.56	0.85	14.58
K				
Calibration	0.54	910.24	0.74	270.15
Validation	0.37	1254.76	0.52	347.52

Table 6
PLS calibration models (cross-validation) to predict sensory panel scores built on the results of the electronic tongue developed at Saint-Petersburg University (a) and the ASTREE electronic tongue (b)

	Slope	Offset	Correlation	RMSEC/RMSECV
(a) Saint-Petersburg University				
Sweetness				
Calibration	0.96	−0.01	0.99	0.22
Validation	0.23	2.86	0.48	1.47
Sourness				
Calibration	0.88	0.41	0.95	0.28
Validation	0.42	2.07	0.76	0.64
Saltiness				
Calibration	1.02	−0.07	0.99	0.06
Validation	0.54	1.65	0.84	0.42
Umami				
Calibration	0.92	0.24	0.99	0.11
Validation	0.20	3.07	0.57	0.80
(b) ASTREE electronic tongue				
Sweetness				
Calibration	0.93	0.09	0.97	0.48
Validation	0.37	2.04	0.80	1.22
Sourness				
Calibration	0.84	0.70	0.92	0.38
Validation	0.36	2.51	0.70	0.69
Saltiness				
Calibration	0.99	0.05	0.99	0.03
Validation	0.55	1.84	0.94	0.41
Umami				
Calibration	0.96	0.04	0.98	0.20
Validation	0.50	1.53	0.85	0.69

3.3. Prediction of individual taste compounds: relating electronic tongue data with instrumental measurements

PLS1 models were built to predict the concentration of two sugars, three acids and two minerals using both electronic tongues. The results of the PLS analysis are shown in Table 5a and b. Since the electronic tongue developed at the University of Saint-Petersburg gives potential readings, the logarithm of the concentration of all compounds is used for the analysis [3]. As shown in Table 5a, this electronic tongue is able to predict the concentration of all sugars, acids and minerals of interest. The PLS models show slopes close to one and low offsets. All slopes are higher than 0.90, except for the validation model of citric acid, and all offsets are close to zero. The correlations between measured and predicted values of all PLS models are high and close to one. Finally, the RMSECV values, which are a measure for the prediction error, are very low. It can be concluded that the calibration and validation models are satisfactory to predict chemical compounds present in a tomato matrix. Validation on a completely independent dataset is required in the future.

The PLS models based on the measurements of the ASTREE electronic tongue are shown in Table 5b. The results are very different from those of the electronic tongue of Saint-Petersburg University. In case of the ASTREE electronic tongue the concentrations of the individual compounds were used in the model. Different transformations of the data, e.g. logarithmic, were tried out in the analysis, but the most satisfactory results were found using raw data. All compounds show PLS prediction models which are not satisfactory. The slopes and offsets of both calibration and validation models are not acceptable. All slopes are

Table 7
Overview of technical information (a) and performance (b) of two multisensor systems

	Electronic tongue Saint-Petersburg University	ASTREE electronic tongue Alpha M.O.S.
(a) Technical information		
Sensors	18 potentiometric sensors and Ag/AgCl reference electrode	Commercial set of seven liquid sensors (set #1)
System handling	Manual	Autosampler
Samples	10 ml of sample + 50 ml of distilled water	90 ml of centrifuged sample
Measurement time	3 min	3 min
Cleaning	7 min using distilled water	20 s using distilled water
Drift of sensors	Small baseline drift	Large baseline drift
(b) Performance		
Classification	Possible, based on sweetness and sourness	Possible, no correlation with taste
Quantification of individual compounds	Sugars, acids and minerals	Not possible
Quantification of taste	Sourness and saltiness	Sweetness, sourness, saltiness and umami

low and the offsets of glucose, fructose and, especially, K are far from zero. The correlations between measured and predicted values of both the calibration and validation models of glutamic acid and Na are acceptable, ranging between 0.80 and 0.94, but they stay lower than the correlations found in the PLS models of the electronic tongue of the University of Saint-Petersburg. The models built for the other sugars, acids and K show correlations that are not sufficient to ensure good predictions. The RMSECV values of all models are in line with the slope, offset and correlation, showing high values for glucose, fructose and K, but also for Na. From these results can be stated that the ASTREE electronic tongue equipped with this set of sensors is not able to predict individual chemical compounds in tomato juices.

3.4. Prediction of tomato taste: relating electronic tongue data with sensory panel evaluation

The potential of both electronic tongues to predict sensory panel scores is studied in a PLS analysis. Models were built using the sensory panel evaluations of sweetness, sourness, saltiness and umami as references. The PLS calibration and validation models of both multisensor systems are shown in Table 6a and b. The electronic tongue developed at the University of Saint-Petersburg gives very good results for all calibration models (Table 6a). All slopes and correlations are close to one and the offsets and RMSEC values are low. The validation models however are not satisfactory for all taste attributes. All validation models show low slopes and high offsets. The correlations found in the PLS models of sourness and saltiness, respectively 0.76 and 0.84, are acceptable, but the correlations between the other two taste attributes, sweetness and umami, and the electronic tongue of Saint-Petersburg University are low with values, respectively 0.48 and 0.57. RMSECV values are low except for the prediction model of sweetness.

The same PLS analysis was performed on the data from the ASTREE electronic tongue (Table 6b). The results of the PLS calibration models between the taste attributes and the ASTREE electronic tongue are comparable to those of the electronic tongue developed at Saint-Petersburg University. All slopes and correlations are again close to one and offsets and RMSEC values are low. The validation models however are different from those shown in Table 6a. The slopes are low and the offsets are high, but the correlations between the ASTREE electronic tongue and sweetness, sourness, saltiness and umami are high, respectively 0.80, 0.70, 0.94 and 0.85. All RMSECV values are low, again except for the prediction model of sweetness. Overall, this electronic tongue seems capable to some extend to predict tomato taste (Table 7).

4. Conclusion

The potential of two electronic tongues to both classify tomato cultivars and quantify their most important taste compounds and taste was evaluated in this paper. Both multisensor systems show considerable differences in measurement protocol. The electronic tongue developed at the University of Saint-Petersburg demands little sample preparation and only a relatively small amount of sample is needed. Cleaning of the sensors takes more time, but because of this the sensors show almost no drift in the time frame of the performed experiment. The commercially available ASTREE electronic tongue requires a large amount of centrifuged sample. The sensor cleaning protocol is rather limited and might results in sensor drift. Both electronic tongues are able to classify tomato cultivars based on their sugar, acid and mineral content. Classification however occurs based on different taste compounds in both systems. The multisensor system developed at Saint-Petersburg University shows a classification of tomato cultivars which is highly correlated to the reference techniques. The discrimination is based on the overall sweet and sour taste of the fruits. The system of Saint-Petersburg University predicts individual compounds in a tomato matrix, while the ASTREE electronic tongue only quantifies the concentration of glutamic acid and Na. This latter system, on the other hand, is capable to some extend to predict tomato taste, as scored by a trained sensory panel.

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