'Artificial Sensory Analysis' for Sensory Classification of Prosecco Sparkling Wines

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Real-time in-process reference to a consolidated standard during sparkling wine production would be beneficial for reducing product loss and/or allowing a timely diagnosis of intervention needs (correction etc). Instead, end-point control by assaying by the oenologist supervising batch production is the only form of (sensory) control normally carried out in wineries. Afterwards, samples from production batches must pass the evaluation step at the Commission's desk.

The present experimental study was carried out to assess whether the responses of an "electronic nose", i.e. a non-specific, gas-phase analytical instrument, is capable to draw an outline of the sensory profile of Conegliano Valdobbiadene Prosecco Superiore DOCG and Prosecco DOC in a way that is objective, repeatable and that can be simply related to the verdict of a group of expert judges.

1. Introduction

Real-time in-process reference to a consolidated standard during sparkling wine production would be beneficial for reducing product loss and/or allowing a timely diagnosis of intervention needs (correction etc). Periodic (but sometimes only end-point) control by assaying by the oenologist supervising batch production and a batch of chemical and physical analyses are normally carried out in wineries. Afterwards, each production batch must be sampled by the producer and must succeed the evaluation step on the institutional side before being legally labellable under the respective denomination. The institutional evaluation comprises a well-defined set of chemical and physical analyses regarding the parameters on which (legal or disciplinary) limits exist and a Commission assay. The Commission assay is only passed if the sample is approved at the analytical assay.

Marketing and technological needs motivate an instrumental monitoring of increased tightness. The consumer increasingly requires high sensory quality product and International markets require large amounts of highly standardised products, where normal batch-to-batch variations which would be denoted as 'typical' in the domestic market, are not acceptable. In order to save production time, defect rejection should begin with the early detection of non compliant batches.

Artificial sensory analysis is an oxymoron, given that equipment does not have senses; however, equipment that feature a limited number of non-specific sensor mimick Nature's senses which derives a large number of sensations from a limited number of receptors. Therefore, the sensor mimicks the receptor, while a mathematical algorithm mimicks brain in recognition and judgement. The researcher should complement the electronic nose (e-nose) sensors with an algorithm and adaption options capable of optimising the recognition capabilities of the system when it is used by an unexperienced operator.

E-noses have found two main fields of application: environmental monitoring (for environmental quality assurance, investigation, and liability; Dentoni et al., 2012, Amodio et al., 2012) and food product characterisation (Peris and Escuder-Gilabert, 2009); in this latter domain inter- (Alexaindre et al., 2009) and intra-varietal (López de Lerma et al., 2013) identification, and real-time process monitoring (Pinheiro et al., 2002; Lozano et al., 2014). In winemaking, on-line fermentation monitoring has been proposed by density measurement, ethanol concentration and CO_2 evolution. Attempts have been made at the on-line measurement of specific by-products (e.g. by biosensors) and quality markers or of several simultaneous products (by FT-IR or E-noses). This objective is highly ambitious, but not unrealistic (Sablayrolles, 2009). However, to the best of the authors' knowledge, no significant implementations of such a system has ever been established in any large scale facility as a production aid tool.

The present study has been carried out to assess whether the responses of an "electronic nose", i.e. a non-specific, gas-phase analytical instrument, is capable to draw an outline of the sensory profile of Conegliano Valdobbiadene Prosecco Superiore DOCG and Prosecco DOC in a way that is objective, repeatable and that can be simply related to the verdict of a group of expert judges.

2. Materials and Methods

2.1 Collection and Measurement of Samples

The analysed samples were supplied anonymously by Valoritalia, the body in charge of assigning DOC and DOCG certifications for Prosecco wines based on their sensory identity. The following type of samples were analysed: Conegliano Valdobbiadene Prosecco Superiore DOCG and Prosecco DOC. Upon tasting, the Valoritalia Commission either approves the batch or suspends the judgement (on the product batch) and states the need of repeating the assessment (MIPAAF, 2011a, 2011b and 2011c). Therefore, samples from re-assessable batches technically failed the sensory test.

The artifical sensory analyses were carried out in a stream of nitrogen, which was used both as a carrier stream (brushing the free surface of the sample in an Erlenmeyer flask), and as the reference substance (Figure 1).
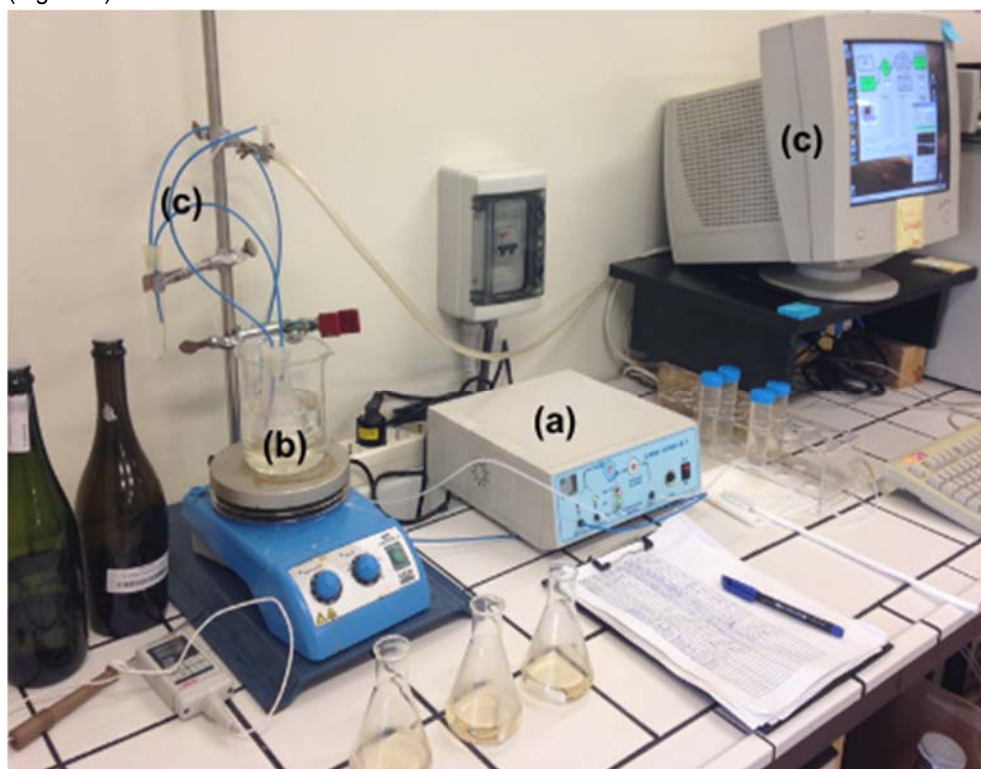

Figure 1: view of the electronic nose sparkling wine sample assaying setup showing (a) the E-nose; (b) the sample assaying chamber (b); the carrier gas and mixture gas piping and the ancillary gas management devices (c); the personal computer deputed to E-nose control (d)

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The electronic nose used throughout the experimentation was a Libra Nose rev. 2.1, featuring multiple quartz micro-balance technology by Tor Vergata University of Roma. Additional input to the classification algorithm was supplied by picking selected analytical data from the set of chemical analyses that is carried out on every sample passing the sensory test. Specifically, the following four measurements relevant to the conditions of the headspace were adopted: volatile acidity, SO_2, CO_2 overpressure and effective ethanol concentration.

Ethanol in the headspace may haircut sensitivity to aromas during fermentation monitoring (Pinheiro et al, 2002). Here ethanol concentration span is limited and effective ethanol concentration was included in the input data to help the statistical discrimination procedure cancel out ethanol concentration effects on the E-nose data.

The responses of the 8 E-nose sensors underwent time shift-neutral domain filtering to identify the steady state responses of the sensorsand and blank reference by subtracting the sensor response on the reference gas to the reading with the sample wine. Following that, the deviations of the sensor responses with respect to the blank were joined with the 4 variables of the chemical analysis related to the condition of the gas phase in contact with the product and the whole set of information was subjected to standardisation and classification analysis.

Additionally, for the purpose of supervised classification, each sample was keyed according to its status of sensory compliance at the Commission's assay. For compliant samples, a further classification information provided by the Commission, that is, 'most aromatic' and 'least aromatic' of each assaying session, was retained. Non compliant samples were keyed as -1, while compliant samples were keyed as '0' and '+1' according to their classification as the 'most' and 'least' aromatic within their assaying session, respectively.

2.2 Data Processing

Classification was carried out in non supervised and supervised manner by using Octave (http://www.gnu.org/software/octave/) on an Ubuntu Linux personal computer. Overall, 124 independent samples (62 DOCG e 62 DOC) were analysed by the date of finalisation of the present article.

Non supervised classification was carried by Principal Component Analysis (by retaining the topmost 2 and 3 components). Supervised classification was carried out by (Fisher) two-dimensional Linear Discriminant Analysis and Partial Least Squares (again, by retaining the topmost 2 and 3 component PLS) using the additional keying information (-1, 0 and +1). Real-time in-process reference to a consolidated standard during sparkling wine production would be beneficial for reducing product loss and/or allowing a timely diagnosis of intervention needs (correction etc).

The main goal of a Principal Component Analysis (PCA) is to identify patterns in data: finding the directions of maximum variance in high-dimensional data and project it onto a smaller dimensional subspace while retaining most of the information. The whole dataset consisting of d-dimensional samples ignoring the class labels was used to compute the 12-dimensional mean vector and the the covariance matrix of the whole data set. Then, the eigenvectors and corresponding eigenvalues were computed, and the eigenvectors were sorted by decreasing eigenvalues. The 2 (2-D PCA) or 3 (3-D PCA) eigenvectors with the largest eigenvalues were taken to form a 12 x 2 (or 12 x 3) dimensional matrix W and this eigenvector matrix was used to transform the samples onto the new subspace. This can be summarized by the mathematical equation $y = W^T x$, where x is a 12 x 1-dimensional vector representing one sample, and y is the transformed 2 x 1 or 3 x 1-dimensional sample in the new subspace.

Linear Discriminant Analysis (LDA) also provides dimensionality reduction. Contrary to PCA, which ignores class labels and aims at maximising the variance in a dataset, LDA computes the directions ("linear discriminants") that represent the axes that maximise the separation between multiple classes. LDA is performed by computing the 12-dimensional mean vectors for the different classes from the dataset and the scatter matrices (between-class and within-class scatter matrix). Then the eigenvectors (e_1, e_2, ..., e_{12}) and corresponding eigenvalues (λ_1, λ_2, ..., λ_{12}) are calculated for the scatter matrices. The eigenvectors are sorted by decreasing eigenvalues and the 2 eigenvectors with the largest eigenvalues are chosen to form a 12×2-dimensional matrix W (where every column represents an eigenvector). This 12×2 eigenvector matrix to transform the samples onto the new subspace. This can be summarized by the mathematical equation: $y = WT \times x$ (where x is a 12×1-dimensional vector representing one sample, and y is the transformed 2×1-dimensional sample in the new subspace).

PLS resembles PCA in that data are transformed, but the transformation is chosen which maximises the correlation with the output data (here, with the single group number) instead internal data variance.

3. Results and Discussion

The data were processed in two ways: in a single cluster, including all the available samples and, separately, for Conegliano Valdobbiadene Prosecco Superiore DOCG and Prosecco DOC samples. The results are shown in Figure 2 and 3.

To date, the available data set is classified at best between compliant and non-compliant samples by using LDA; indeed, non compliant samples can be separated from compliant ones for both denominations. PLS could only produce well visible clusters for DOCG samples when three latent variables were used (Figure 3). PCA did not produce visible clustering in either 2- (Figure 4) or 3-score plots.

The loadings (not reported for lack of space) consistently show that the E-nose contribution is most evident in the second (a diversified contribution) rather in the first data display direction (a stronger, but more uniform contribution).

A moderate separation, with a significant overlapping band, was obtained between samples classified as the 'most' and the 'least' aromatic within each day's assaying pool. This reflects the fact that the 'most aromatic' sample of one day may be less aromatic than the least aromatic of a different day, or vice versa.

In no case the sole contribution of either the electronic nose or the physico-chemical analysis of the gas phase was sufficient to create a recognisable separation of compliant from non compliant samples.

Sensory assessment by jury is highly variable, as judges themselves sometimes declare, and this occurs over time even within a single Commission see because the experts involved as different judges are generally involved from one day to another (it should be noted here that the sensory assessment that is performed by this type of Commissions is not a quantitative sensory analysis; this explains quite a bit of the scarce reproducibility problem).

When large DOC areas are involved the summed effect of product variability (as an effect of the pedoclimatic factors) and jury board variability over multiple assaying commissions may have quite a profound effect on the outcome of the assessment procedure itself.

DOCG entails a stricter control over the product, and DOCG areas are generally smaller than DOC ones, so that the uniformity problem is minimised.

An automatic system might help in keeping a pre-defined track of hedonistic expectation, but only human perception may express a value and is rightfully free to evolve over time, so that the pre-defined track should be able to adaptively evolve over time following the long-term man's preference evolution.
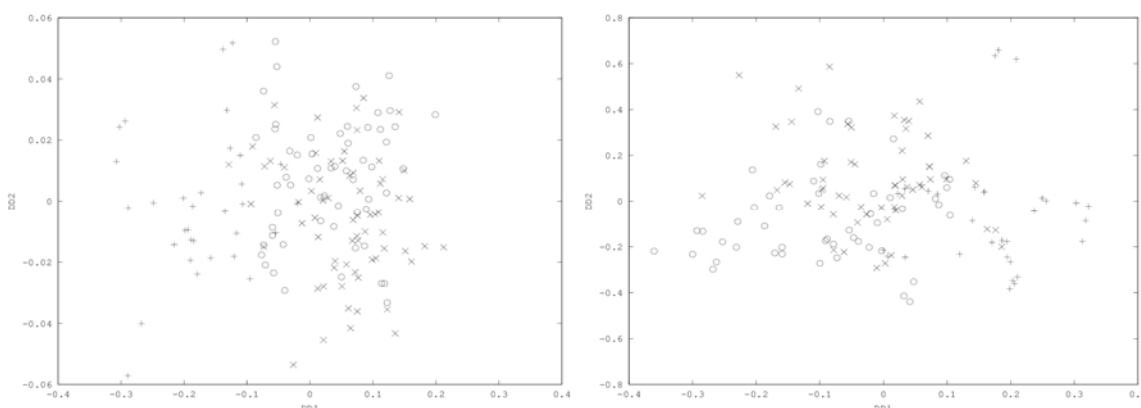

Figure 2: Classification analysis by LDA of DOCG (left) and DOC (right) samples. +: non conformant samples; x: most aromatic samples of the session; o: least aromatic samples of the session.
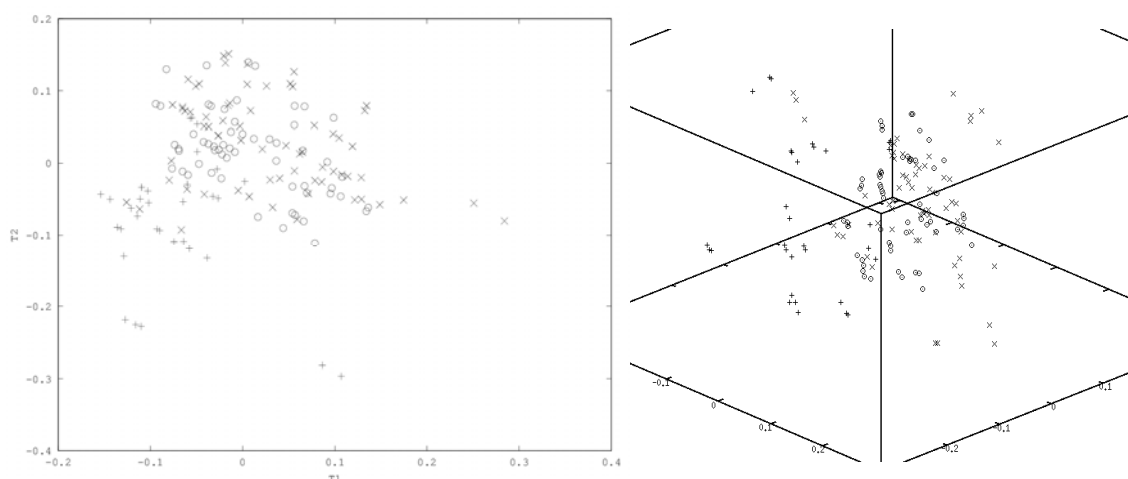
Figure 3: Classification analysis by 2-D (left) and 3-D (right) PLS of DOCG samples. +: non conformant samples; x: most aromatic samples of the session; o: least aromatic samples of the session.
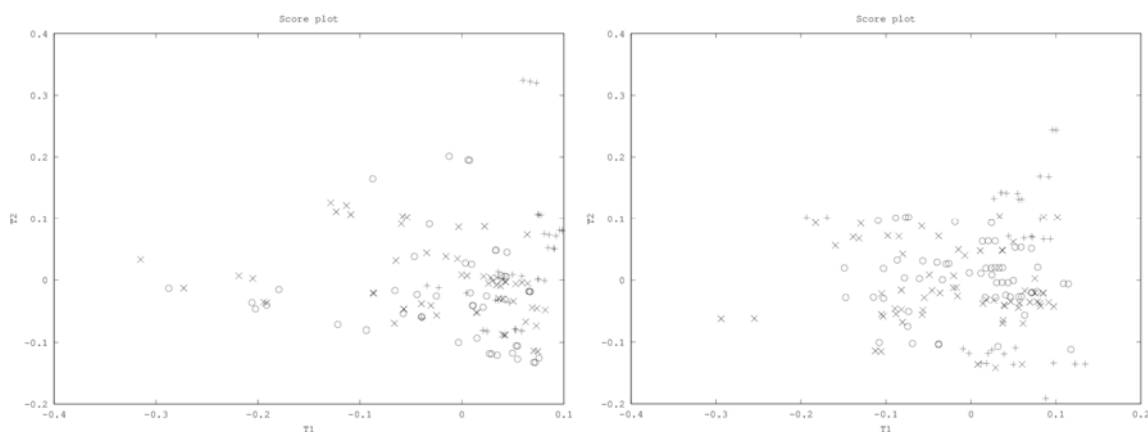

Figure 4: Classification analysis by PCA of DOCG samples (left) and DOC samples (right). +: non conformant samples; x: most aromatic samples of the session; o: least aromatic samples of the session.

4. Conclusions

The electronic nose and some routinely acquired analytical data permit the fast classification of cases of non compliance without the intervention of an expert assayer for DOCG Conegliano Valdobbiadene Prosecco Superiore wines. The generalisation of this result to Prosecco DOC wines requires further research and a higher number of non compliant samples. The discrimination capacity in a winery may be expected to be even higher, given that the samples that reach the Commission have presumably passed the assay at the producer's site with a positive outcome.

For automatic, or semi-automatic sensory control of winemaking to become reality a number of issues must be solved, such as: (1) providing a reference path and acceptability limits for instrumentally-measured hedonistic tone; (2) setting-up a signalling policy for deviations from the reference path and discriminating those that have an identified cause (that is, one which can be assigned with a given level of likelyhood) from those which have an unidentified cause (that is, one has multiple possible causes or which cannot be assigned a cause). It is likely that the assessment of dependability of such a system would require that the oenologist to be called upon signalling, and this latter to perform the required action on the product batch. However, once a highly dependable system comprising (1) and (2) had been set up, a system also including (3) a manipulation system for the surely assigned actions might be conceived and set-up.

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