

On the importance of odour threshold to identify molecules responsible for the odour of a material

Montreer P.¹, Cariou S.¹*, Janaqi S.², Chaignaud M.³, Betremieux I.⁴, Gomez E.⁵, And Fanlo J.L.^{1.3}.

¹ Ecole des Mines d'Alès, Laboratoire Génie de l'Environnement industriel, 6 av. de Clavières, F-30319 Ales Cedex, France

² Ecole des Mines d'Alès, Laboratoire Génie Informatique et Ingénierie de Production, 6 av. de Clavières, F-30319 Ales Cedex, France

³ Olentica SAS, 17 rue Charles Peguy, F-30100 Ales, France

⁴ Total S.A, 2, place Jean Millier, La Défense 6, 92078 Paris La Défense Cedex, France

⁵ Hutchinson S.A., Centre de Recherche, Rue Gustave Nourry, 45120 Châlette-sur-Loing, France

*corresponding author:

e-mail : stephane.cariou@mines-ales.fr

Abstract

In the industrial environment, materials with unpleasant smell are a major problem. Indeed, the odour is one of the most important criteria in the selection, the purchase and the use of a material. An unpleasant odour can cause the rejection of the material by the consumer. Odour control is therefore an important industrial and economic issue. The difficulty is to combine physico-chemical and olfactometric data to identify chemical compounds responsible for the odour. Nowadays, the relationship between these two kinds of data is realized by an expert with his own knowledge.

The identification efficiency of the concerned compounds depends on the expertise level. So, to decrease the result interpretation uncertainty, the aim of this project is to develop a protocol allowing to identify compounds of interest in the entire physico-chemical analysis results. This protocol will be developed in the form of an automated toolbox which combines statistical techniques. This identification should be as exhaustive as possible to identify compounds responsible for odour concentration and/or acceptability and/or quality. This tool will allow enhancing the reliability of the odorous compounds identification, realised by expert to this day.

Keywords: Odour, materials, data mining, modelling

1. Introduction

All materials emit compounds in the air. Sometimes, the mix of compounds or just one of these compounds is responsible for an unpleasant odour associated to these materials [(NESA *et al.*, 2004), (WYPYCH, 2013); (ROGNON and POURTIER, 2014)].

This unpleasant odour could be linked to different dimensions of the odour as odour concentration, acceptability and/or quality [(AFNOR, 1996); (GOURONNEC, 2000); (AFNOR, 2003); (GOURONNEC, 2004)].

However, people use to associate an unpleasant odour with a health hazard but this is not justified. Indeed, many compounds are odorless at their concentration in the air (particularly indoor air) but are not insignificant for the health and vice versa (PIERUCCI *et al.*, 2005).

Despite that, an unpleasant odour implies a rejection of a material and then economic issues. This rejection can also be due to a disgust feeling.

Given the negative impact of the unpleasant odour of a material on people, there is a need of control and work on this odour. To solve this problem the key step is the identification of the compounds responsible for the odour (MEIERHENRICH *et al.*, 2005).

Currently, this work is realized by an expert. The expert in charge of the compounds identification might be an odour expert or the most appropriate person in a firm to deal with this issue (chemist). So with his knowledge, each expert develops his own approach (SEZILLE *et al.*, 2014).

A frequent approach applied is a Gas Chromatography simultaneously associated with an olfactometry analyses (GC-O) (FERNANDEZ *et al.*, 2009). And, others approaches realized by odour expert consist in dealing with a lot of different kinds of data (by their nature, size, source and precision). So, the main difficulty is to manage to match up these data in the most pertinent and exhaustive way.

In this way, all of these approaches present some drawbacks, which are sources of the identification result (CHOLLET and VALENTIN, 2000). Some drawbacks are linked to the expert and some of them are linked to the data.

Indeed, about the expert, the variability is linked to the fact that there is a disparity in skills from one expert to another (CHOLLET and VALENTIN, 2000). Furthermore, at equal competences, the analysis sharpness of the physicochemical spectra could be a source of variability too. In addition, this approach is a time-consuming analysis and creates a dependency of the manufacturer on the expert about this issue.

The aim of the ongoing project is to develop an automated methodology to remedy the expert work heterogeneity. The assets of this methodology are data treatment standardization, time saving and independence of the company.

As the data used and crossed by the expert are the pillars of the work of identification, it's necessary to ensure their completeness, accuracy and reliability.

In this paper the methodology implemented in the project and the importance of data treatment (especially odour detection threshold bibliographic data) are described.

2. Methodology

2.1. Data collected and used by the expert

In response to odour issue, the expert has to manage several data sources.

When an unpleasant odour is detected, the compounds emitted are sampled and analyzed.

Firstly, the air sample is analyzed by GC-MS to identify its composition: the nature and the concentration of each compound. Then the expert collects physico-chemical data.

Secondly, the air sample is analyzed by olfactometry to characterize the odour by its dimensions. Then, the expert collects olfactometric data.

Thirdly, the expert has to use bibliographic data to use parameters of compounds.

The expert will then juggle with all that flow of information to identify, in the most exhaustive way, compounds responsible for the odour.

But the issue is the fact that, beside the variability of the identification due to the expert, there is a variability linked to the data source.

Indeed, the quality of physico-chemical data by GC-MS, depends on the quality of separation, quantification and identification of the compounds. Concerning olfactometric data, the variability is due to the subjectivity of the sensorial analysis. The other source of variability is linked to the lack of homogeneity and completeness of bibliographic data and more particularly odour detection threshold (ODT) data. This last parameter is the identification key of compounds responsible for the odour. Indeed, it's the minimal concentration that is required to detect the odour of a compound. Bibliographic data of ODT presents a low reliability, when data are available.

It is difficult to work on the variability due to physicochemical or olfactometric analysis but it's possible to work on the variability and completeness of bibliographic data all the more that this is the key of the identification.

2.2. Software of treatment

The ODT values of literature are collected on the Excel software and the improvement work of the reliability and the completeness of bibliographic data is realized on the R software (version 3.3.1 - 64-bit).

3. Bibliographic data treatment

3.1. Improvement of reliability of available bibliographic data

As it's explained below, the ODT value available in the literature are marred by a high variability. To illustrate this variability, the case example of the butyl acetate compound is presented in the Table 1 (VAN GEMERT, 2011).

Table 1 : Butyl acetate ODT values in the literature (VanGEMERT, 2011)

Authors	Butyl Acetate ODT values (mg/m ³)
Jung-1936	0.044
May-1966	35.000
Köster-1971	480.000
Hellmann&Small-1973-1974	0.030
Dravnieks-1974	3.000
Anon-1980	0.320
Naus-1982	0.700
Nagy-1991	1.000
Patterson&al-1993	7.700
CM&C et CM -1994	11.500
Zimer&al-2000	0.061
Nagata-2003	0.077
CM&al-2004	0.015
Cain&Schmidt-2009	0.010

The sources of variability can be explained by a lot of parameters as authors 'nationalities or the country normalization. More specifically, variability could be linked to the olfactometric analysis type because of the expected answer type (DRAVNIEKS and PROKOP, 1975), the dilution rate direction [(FALCY and MALARD, 2005); (UENO et al., 2009)], the panel recognition rate (LEONARDOS et al., 1969). The variability could also be linked to the sample quality (FALCY and MALARD, 2005), the chosen compounds to the panel selection : one compound in Europe (AFNOR, 2003) and five compounds in Japan (UENO et al., 2009), the panel subjectivity [(DRAVNIEKS and PROKOP, 1975); (FALCY and MALARD, 2005); (LEONARDOS et al., 1969)], the environmental conditions or the panel applied correction : Odour intensity correction (UENO et al., 2009) or the retrospectively sorting (AFNOR, 2003).

Once available data is cleaned, the second step of work on bibliographic data is the completeness of ODT values for compounds with any ODT values.

3.2. Completeness of bibliographic data

In the litterature, some authors have studied just one compounds whereas others have studies a lot of compounds. Furthermore, some compounds are solely informed by one authors whereas others compounds are informed a lot of time. The ODT database total missing value proportion is 99% (on 1238 compounds) and the proportion of compounds informed at least by one author is 53%. This proportion encourages to use predictive modelling to complete the bibliographic database.

To apply this modelling, the first constraint is finding dimensions which have a potential impact on the odour of compounds and more particularly on their ODT values. Some dimensions are identified as molecular weight, vapor pressure, lipophility or polarity (MEIERHENRICH *et al.*, 2005) but these dimensions are, along with ODT, marred with an important amount of incompleteness and, sometimes, variability.

That's why, the most appropriate solution found is to use QSAR/QSPR (Quantitative Structure-Activity Relationship/Quantitative/Structure-Property Relationship) approach. Indeed, this approach allows to predict physical dimensions (property, activity) from structural index (ROY *et al.*, 2015). Using this aproach allows working wih a complete base of prediction.

This approach is used in many different domains and in many different applications as the mosquito repellent potency of a compound [(MA *et al.*, 1999); (NATARAJAN *et al.*, 2005); (BASAK *et al.*, 2007)], the hydrocarbon compounds dipole moment study (NESTEROV *et al.*, 2004), the ketones acidity study (YUAN *et al.*, 2012), the alkanes boiling point (RAWAT and SATI, 2013) or to the new medicinal compounds mading (GOULON-SIGWALT-ABRAM, 2008)].

The reason why this approach is selected is the fact that the odour encoding reside in the recognition substrate/receptor (DE MARCH, 2015) and that the molecular complexity would determine the acceptability and the olfactory notes quantity (KERMEN *et al.*, 2011). Some authors have already worked on the subject [(DEMOLE and STOLL, 1964); (ZARZO, 2012)] and tried to model the ODT values from QSAR/QSPR approach [(CZERNY *et al.*, 2011); (XU *et al.*, 2012); (PAL *et al.*, 2014); (TOROPOV *et al.*, 2016)]. However, in these studies, the number of compounds is low and specific compounds are often chosen. In the present project, the aim is to generate the approach for wathever compounds.

Then, a predictive modelling will be apply according to a QSAR/QSPR approach with the best statistical methodology. Some statistical treatments can be identified as potential solution as Partial least square regression, Support Vector Matrice or Neural Network. Furthermore, a sorting of index can also be applied in parallel.

Thus, at this step, the obtention of a reliable and complete ODT database will improve the expert work , but its own variability has to be resolved by other tools. The aim for the future step is to automate the work of the expert.

4. Automation of the work of expert

This automation is realized with a toolbox which allows weighting the concentrations of each compound from the physico-chemical data by its own ODT value (the ODT values are now available for all compounds with varying degrees of accuracy thanks to the previous steps). Then, the obtained data is combined to olfactometric data to identify a bouquet of compounds for each odour dimension.

This toolbox will be developed on a synthetic gaseous mixture of about 50 compounds. This mixture will be used to eliminate physico-chemical data uncertainty. Indeed, the nature and the chemical concentration of each compound are well-controlled. Furthermore, the toolbox efficiency could be tested.

The result of the automated approach will be then compared to the expert approach to judge the accordance between the two approaches and validate the toolbox efficiency.

5. Evaluation of needed precision on olfactometric and physico-chemical data by materials application

The aim of this part is evaluating the precision of physicochemical and olfactometric data required to have a good result on materials samples.

Indeed, for physico-chemical data, the purpose is to evaluate the improvement of the separation, the quantification and the footprint qualities on the identification result, with different techniques: TD-GC-MS, TD-GC2D-MS and PTR-MS (Figure 1).

For the olfactometric data, the purpose is to evaluate the potential precision gain with an increase of the jury size (6, 12 and 18).

This approach will allow to rule the analysis quality on the final result about the identification of the potential compounds responsible for the materials odour.

6. Conclusion

To conclude, the methodology is structured into four steps:

- A work of ODT database implementation and reliability,
- A complementary work of this ODT database improvement and completeness,
- The development of an automatic method based on statistical toolbox to link odour characteristics to compound or group of compounds responsible of odour,
- An evaluation of the required physico-chemical and olfactometric analyses accuracies on the identification work.



Figure 1 : Precision of physico-chemical data analysis

References

AFNOR, 2003. Norme NF EN 13725.

- AFNOR, 1996. Norme NF X43-103 : Qualité de l'air. Mesurage de l'odeur d'une atmosphère gazeuse. méthode supraliminaire.
- BASAK, S.C., NATARAJAN, R., NOWAK, W., MISZTA, P., KLUN, J.A., 2007. Three dimensional structure-activity relationships (3D-QSAR) for insect repellency of diastereoisomeric compounds: a hierarchical molecular overlay approach. SAR and QSAR in Environmental Research 18, 237–250. doi:10.1080/10629360701303784
- CHOLLET, S., VALENTIN, D., 2000. Le degré d'expertise a-t-il une influence sur la perception olfactive? Quelques éléments de réponse dans le domaine du vin. L'année psychologique 100, 11–36. doi:10.3406/psy.2000.28625
- CZERNY, M., BRUECKNER, R., KIRCHHOFF, E., SCHMITT, R., BUETTNER, A., 2011. The Influence of Molecular Structure on Odor Qualities and Odor Detection Thresholds of Volatile Alkylated Phenols. Chemical Senses 36, 539–553. doi:10.1093/chemse/bjr009
- DE MARCH, C., 2015. Modélisation des mécanismes moléculaires de la perception des odeurs. PhD of Université Nice Sophia Antipolis.
- DEMOLE, E., STOLL, D.M., 1964. Synthèse et relations entre constitution chimique et odeur dans la série des terpényl-3-cyclohexanols. Helvetica chimica acta 47, 1766–1774. doi:10.1002/hlca.19640470713
- DRAVNIEKS, A., PROKOP, W.H., 1975. Source Emission Odor Measurement by a Dynamic Forced-Choice Triangle Olfactometer. Journal of the Air Pollution Control Association 25, 28–35. doi:10.1080/00022470.1975.10470045
- FALCY, M., MALARD, S., 2005. Comparaison des seuils olfcatifs de substances chimiques avec des indicateurs de sécurité utilisés en milieu professionnel. Hygiène et Sécurité au travail- Cahier de notes documentaire (La revue technique de l'INRS) pp7-21.
- FERNANDEZ, X., BREME, K., VARLET, V., 2009. Couplage chromatographie en phase

gazeuse/olfactométrie. Techniques de l'ingénieur. Analyse et caractérisation 1, 1–5.

- GOULON-SIGWALT-ABRAM, A., 2008. Une nouvelle méthode d'apprentissage de données structurées: applications à l'aide à la découverte de médicaments. PhD of Université Pierre et Marie Curie-Paris VI.
- GOURONNEC, A.-M., 2004. Analyses olfactométriques ou mesure des odeurs par analyse sensorielle. Ed. Techniques Ingénieur.
- GOURONNEC, A.-M., 2000. Mesure des odeurs par analyse sensorielle ou «olfactométrie». Pollution atmosphérique 583–598.
- KERMEN, F., CHAKIRIAN, A., SEZILLE, C., JOUSSAIN, P., LE GOFF, G., ZIESSEL, A., CHASTRETTE, M., MANDAIRON, N., DIDIER, A., ROUBY, C., BENSAFI, M., 2011. Molecular complexity determines the number of olfactory notes and the pleasantness of smells. Scientific Reports 1. doi:10.1038/srep00206
- LEONARDOS, G., KENDALL, D., BARNARD, N., 1969. Odor Threshold Determinations of 53 Odorant Chemicals. Journal of the Air Pollution Control Association 19, 91–95. doi:10.1080/00022470.1969.10466465
- MA, D., BHATTACHARJEE, A.K., GUPTA, R.K., KARLE, J.M., 1999. Predicting mosquito repellent potency of N, N-diethyl-m-toluamide (DEET) analogs from molecular electronic properties. The American journal of tropical medicine and hygiene 60, 1–6.
- MEIERHENRICH, U.J., GOLEBIOWSKI, J., FERNANDEZ, X., CABROL-BASS, D., 2005. De la molécule à l'odeur. L'actualité chimique 289, 29.
- NATARAJAN, R., BASAK, S.C., BALABAN, A.T., KLUN, J.A., SCHMIDT, W.F., 2005. Chiral index, molecular overlay and biological activity of diastereoisomeric mosquito repellent. Pest Manag Sci 1193–1201. doi:10.1002/ps. 1116
- NESA, D., CROCHEMORE, S., COUDERC, S., 2004. Analyse sensorielle des matériaux d'habitacle automobile : Olfaction. Ed. Techniques Ingénieur.
- NESTEROV, I.V., TOROPOV, A.A., DUCHOWICZ, P.R., CASTRO, E.A., 2004. An Improved QSPR Modeling of Hydrocarbon Dipole Moments. The

Scientific World JOURNAL 4, 956–964. doi:10.1100/tsw.2004.193

- PAL, P., MITRA, I., ROY, K., 2014. QSPR Modeling of Odor Threshold of Aliphatic Alcohols Using Extended Topochemical Atom (ETA) Indices. Croatica Chemica Acta 87, 29–37. doi:10.5562/cca2284
- PIERUCCI, P., PORAZZI, E., MARTINEZ, M.P., ADANI, F., CARATI, C., RUBINO, F.M., COLOMBI, A., CALCATERRA, E., BENFENATI, E., 2005. Volatile organic compounds produced during the aerobic biological processing of municipal solid waste in a pilot plant. Chemosphere 59, 423–430. doi:10.1016/j.chemosphere.2004.10.040
- RAWAT, S., SATI, O.P., 2013. Quantitative structure property relationship study for prediction of Boiling point of aliphatic alkanes. International Journal of Pharmacy and pharmaceutical science 5, 107–109.
- ROGNON, C., POURTIER, L., 2014. Les odeurs dans l'environnement. Ed. Techniques Ingénieur.
- ROY, K., KAR, S., DAS, R.N., 2015. Statistical Methods in QSAR/QSPR, in: A Primer on QSAR/QSPR Modeling. Springer International Publishing, Cham, pp. 37–59. doi:10.1007/978-3-319-17281-1_2
- SEZILLE, C., FOURNEL, A., ROUBY, C., RINCK, F., BENSAFI, M., 2014. Hedonic appreciation and verbal description of pleasant and unpleasant odors in untrained, trainee cooks, flavorists, and perfumers. Frontiers in Psychology 5. doi:10.3389/fpsyg.2014.00012
- TOROPOV, A.A., TOROPOVA, A.P., CAPPELLINI, L., BENFENATI, E., DAVOLI, E., 2016. Odor threshold prediction by means of the Monte Carlo method. Ecotoxicology and Environmental Safety 133, 390– 394. doi:10.1016/j.ecoenv.2016.07.039
- UENO, H., AMANO, S., MERECKA, B., KOSMIDER, J., others, 2009. Difference in the odor concentrations measured by the triangle odor bag method and dynamic olfactometry. Water Science and Technology 59, 1339.
- VAN GEMERT, L.J., 2011. Odour Thresholds, OPP-Oliemans Punter&Partners BV. ed. Zeist, The Netherlands.
- WYPYCH, G., 2013. Handbook of Odors in Plastics Materials, ChemTec Publishing (CP). ed. Toronto.
- XU, X., LUAN, F., LIU, H., GAO, Y., 2012. Prediction of the odor thresholds of oxygen and nitrogen containing heterocycles using the quantitative structure-property relationship approach. Asian Journal of Chemistry 24, 3842.
- YUAN, Y., MOSIER, P.D., ZHANG, Y., 2012. Quantitative structure-property relationship (QSPR) model for predicting acidities of ketones. Journal of Biophysical Chemistry 3, 49–57. doi:10.4236/jbpc.2012.31007
- ZARZO, M., 2012. Effect of Functional Group and Carbon Chain Length on the Odor Detection Threshold of Aliphatic Compounds. Sensors 12, 4105–4112. doi:10.3390/s120404105