Title:

Artificial Olfaction: bio-inspired approaches for tackling sensor drift issue

Authors & affiliations:

S. Di Carlo[1], M. Falasconi[2], E. Sanchez[1], G. Sberveglieri[2], A. Scionti[1], G. Squillero[1], A. Tonda[1]
[1] Control and Computer Engineering Department, Politecnico di Torino, Torino, Italy
[2] SENSOR, University of Brescia & CNR-IDASC, Brescia, Italy
Presenting author: matteo.falasconi@ing.unibs.it

Abstract: (Your abstract must use **Normal style** and must fit in this box. Your abstract should be no longer than 300 words. The box will 'expand' over 2 pages as you add text/diagrams into it.)

Artificial Olfaction (AO) is a rather topical branch of bio-inspired artificial intelligence with formidable challenges and potential impacts. A robot equipped with an Electronic Nose (EN) could have tremendous implications, for instance assisting humans in security issues such as detecting toxic gases or searching explosives [1].
Despite progresses made in the last ten years, an AO system able to mimic the human olfaction capabilities is still a dream for researchers. However, ENs might represent in the near future a simple, fast, high throughput and economic alternative to conventional analytical instruments and traditional techniques for routing quality controls of the food industry [2], [3].
To realize that scenario some technological challenges must be still overcome. Chemical sensors drift is one the issues that mainly limits the ENs adoption in real industrial setups due to high recalibration efforts and costs [4]. Indeed, pattern recognition (PaRC) models typically used to analyse EN data become useless after a period of time, in some cases a few weeks, requiring frequent and costly calibration phases.
Although drift mitigation strategies date back to the early 90s, there is need of new approaches, such as adaptive drift correction methods able to adjust the PaRC model in parallel with data acquisition. Self-Organizing Maps (SOMs) and Adaptive Resonance Theory (ART) networks have been already tested in the past with fair success.
In this paper we will present and discuss an original methodology based on Covariance Matrix Adaptation Evolutionary Strategy (CMA-ES) [5]. CMA-ES is a stochastic optimization technique that implements mechanisms inspired by biological evolution: candidate numerical solutions play the role of individuals in a population and are subjected to the rules of the game (reproduction, mutation, recombination, natural selection and survival of the best fitting individuals).

The proposed drift correction algorithm is summarized in Figure 1. The basic idea is to adaptively correct the drift within "short" time windows (such that linear drift can be assumed) to extend the validity of the classification model built in the training phase. The correction is applied through a linear transformation represented by a Correction Matrix (CM). CM is updated by continuously and slowly evolving over time the linear transformation parameters.
The adaptation obtained through the CMA-ES, aims at minimizing the sum of the distances of each classified sample from the centroid of the related training class. This objective function measures how much the drift-corrected samples deviate from the class distributions learnt during the calibration phase.
The proposed methodology was validated both on simulated and experimental data sets obtained at SENSOR lab with a prototypal EN named EOS835 [6]. Experimental measurements consist of 545 samples of 5 organic vapors measured by static headspace sampling. Four cross-validated classifiers were tested: kNN, PLS, ANN and Random Forest (RF). Orthogonal Signal Correction (OSC) based drift correction was used as state of the art comparison technique.
The self-adaptive CMA-ES approach showed fine results and superior performance, especially in the long term, if compared to classical OSC correction (Figure 2).
Our findings corroborate the hypothesis that CMA-ES can systematically adapt to drift even when the amount of data is relatively small. CMA-ES can also flexibly work well

with different types of classifiers that may clearly affect absolute classification performance (compare for instance the results of kNN and RF shown in Figure 2).

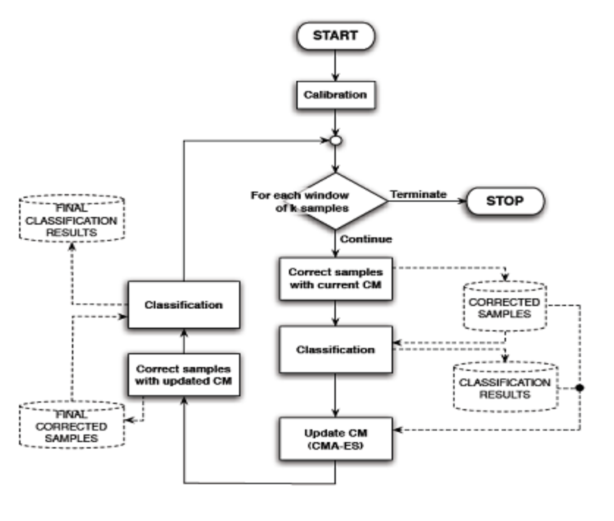

Figure 1. Conceptual flow chart of the algorithm.

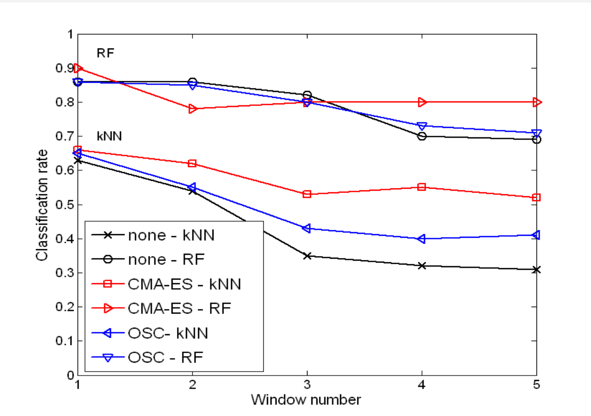

Figure 2. Classification results on drift corrected data at different time frames.

[1] Xiao Jun Zhang et al., 2010, Advanced Materials Research, 2150, 139-141;
[2] Zhang Z. et al., 2008, Journal of Bionic Engineering, 5(1), 67-73;
[3] Zheng X.Z. et al., 2009, Journal of Bionic Engineering, 6(3), 290-297;
[4] Padilla, M. et al., 2010. Chem. and Int. Lab. Systems 100 (1), 28 – 35;
[5] Lozano, J. A. at al., 2006. Studies in Fuzziness and Soft Computing. Vol. 192, Ch. 4, pp. 75–102 (Ed. Springer);
[6] Pardo, M., Sberveglieri, G., 2004. MRS Bulletin 29 (10), 703–708.