Application of multiplicative drift correction and component correction methods on simulated gas sensor array responses*

Paweł KALINOWSKI, Grzegorz JASIŃSKI†

Keywords: gas sensors; long term stability; drift compensation

Abstract: Sensor response drift is one of the most challenging problems in gas-analyzing systems. Such systems, commonly called electronic noses, are expected to be reliable and reproducible in the long term. Due to the drift phenomena, electronic noses usability is limited to the relatively short period of time, and frequent recalibrations of the device are required. Since it is very hard to fabricate sensors without drift, this phenomenon has to be detected and can be compensated using signal processing methods in order to extend sensor array operation time. In this work, two approaches for drift compensation, namely the Multiplicative Drift Correction and Component Correction methods, are presented. An analysis of the simulated gas sensor array response is shown.

1. Introduction

Artificial olfaction systems, commonly referred to as electronic noses, are instruments designed for precise detecting and determining volatile compounds. In such systems, usually an array of partially selective gas sensors is used. The array generates a characteristic fingerprint response for specific gases, which can be recognized using feature extraction and pattern recognition techniques (Scott et al., 2007). Electronic noses represent a potentially low-cost and fast alternative for conventional analytical instruments, like gas chromatographs, and can be successfully used outside laboratories, e.g. in applications for air-contaminant monitoring. However, applications of gas-analyzing systems which are using gas sensor arrays as a detector are still limited. One of the most challenging problem, which limit such devices for being used in real industrial systems is lack of their stability caused by a signal drift of the sensors.

Drift is the gradual change in any quantitative characteristics that is supposed to remain constant. It means that the drifting sensor does not give exactly the same response even if it is exposed to the same environment for a period of time. There

*This work was partially supported by the National Centre for Research and Development, project LIDER No. 22/103/L-2/10/NCBiR/2011

†Gdansk University of Technology, Department of Biomedical Engineering, ul. Gabriela Narutowicza 11/12, 80-233 Gdańsk Wrzeszcz, Poland, e-mail: pawkalin88@gmail.com

are a few causes of the drift phenomenon. Drift can be caused by the processes in sensors (like poisoning, aging) or related to the measurement system – i.e. influence of temperature and humidity on sensors responses. It is a common problem for all chemical sensors which has to be considered if the measurements are made for a long period of time (Holmberg and Artursson, 2003). It is very hard to fabricate sensors resistant to the drift phenomenon, therefore it must be detected and compensated using drift mitigation algorithms in order to achieve reliable measurements (Di Carlo and Falasconi, 2012).

2. Drift compensation methods

So far, several methods for drift mitigation have been developed and published. They can be divided into four groups, namely sensor signal preprocessing methods, periodic calibration, attuning and adaptive methods. Methods which belong to the group of periodic calibration provide promising results for commercial electronic noses. They are also an attractive solution for the drift mitigation problem due to their relative simplicity of implementation (Di Carlo and Falasconi, 2012).

The periodic calibration approach is based on the estimation of the drift in the e-nose system to be later removed. The drift estimation and counteraction can be realized in a univariate or multivariate way. In the univariate approach, drift is compensated in each sensor in array individually. The Multiplicative Drift Correction method (MDC) is an example of the univariate approach. In the multivariate approach, the direction of the drift is estimated basing on the responses of the whole array. In fact, the drift counteraction is performed in the feature space, obtained e.g. by using Principal Component Analysis (PCA) on the array responses. The Component Correction method (CC) is an example of the multivariate approach.

2.1. Multiplicative Drift Correction

The idea of the MDC method is to estimate the direction of the drift for each individual sensor in array. It is achieved by frequently measuring calibration samples and obtaining a series of measurements. The temporal changes in a series of measurements are indicating the direction of the drift in sensor. By building a regression model on the series, it is possible to calculate the correction factor which enables the removing of the drift from the signal by multiplying each measurement through the estimated factor. This procedure can be realized in the short- and long-term measurements. The detailed description of calculating procedures for the MDC method can be found elsewhere (Haugen et al., 2000).

2.2. Component Correction

In the CC method, the direction of the drift is estimated in the responses of the whole sensor array. Gas measurements contain a lot of redundant information, which can be easily compressed by performing Principal Component Analysis on the measured data. In PCA the original data matrix $\mathbf{X}$ is transformed into two new matrices – scores $\mathbf{T}$ and loadings $\mathbf{P}$. The score matrix contains the coordinates of original observations in the space represented by principal components, while the loading matrix is the projection matrix, onto which the data from $\mathbf{X}$ are projected to obtain values of $\mathbf{T}$. Usually, the first few Principal Components (scores, and loadings corresponding to them) contain the most significant information from the original data (Wold et al., 1987).

The component correction method is based on the assumption that if sensors in array have significant drift, the first principal component from the PCA analysis describes the direction of this drift. Information about drift can be obtained from the first loading vector **p** from reference measurements. The drift direction is assumed to be the same also for further measurements. The correction is performed by removing this component from measurements, which indicates the direction of drift. The CC procedure was developed and published by Artursson et al. (2000).

3. Simulations

Illustration of the effects of using the MDC and CC methods is shown in this work on simulated gas sensor array responses. Simulations were performed in Matlab (Mathworks, Inc.). For the PCA analysis, the routines from Statistics Toolbox were used. The simulated sensor array is shown in Fig. 1. Baseline sensors signal levels were estimated on the basis of the individual sensors datasheets, also verified by our previous measurements of the presented array. Simulated sensor responses for synthetic air (a reference gas) were equal: TGS 2106 – 19 kΩ, TGS 2602 – 180 kΩ, TGS 2180 – 150 kΩ, TGS 825 – 30 kΩ, TGS 826 -25 kΩ, TGS 812 – 19 kΩ. Additionally, to each individual signal fluctuations were added (normally distributed pseudorandom numbers). This was done because of the fact, that measured sensors responses are usually not exactly the same in a period of time – they vary due to the impact of such factors as humidity, temperature or because of inaccuracies in the measurement system.

Fig. 1. An array of sensors whose responses have been simulated.

To demonstrate the effects of using both presented drift counteraction methods two slightly different simulation cases have been proposed. The simulated sensor signals in both cases have been generated to obtain collection of 3000 measurement points. The initial signals represent sensor responses without a drift phenomenon. Drift was added to signals after the established time. The results and detailed description of both simulation cases are shown in the next paragraph.

4. Results and discussion

The first simulation case was performed to show the effects of using the Multiplicative Drift correction method. In Fig. 2 generated sensors signals are presented. In Fig. 2 a) responses for synthetic air and another hypothetical volatile compound are shown. The presented simulation shows a simplified response to the presence of gas by exhibiting only the steady-state response of sensors. 1500 generated measurement points represent the responses without drift. The initial values of responses are treated as reference measurements in the procedure of estimating the drift direction. The linear drift (a gradually decreasing or increasing signal of sensors) was generated during the last 1500 simulated measurement points. In Fig. 2 b) the array response for synthetic air and simulated gas after performing the PCA method is illustrated. In this figure reference classes (responses from first 1500 points) can be seen as red and blue clusters. Generated drift caused a shift of array responses (green and light blue clusters) for specific compounds from reference clusters. This may cause misclassifications – the training model for a classification purpose becomes useless in a relatively short period of time.

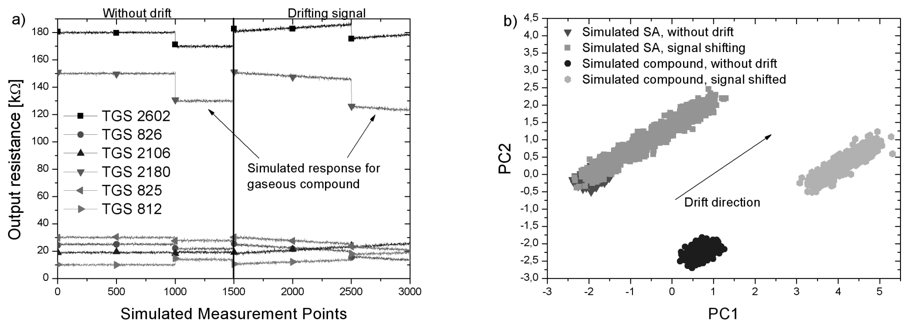

Fig. 2. a) Responses of six simulated TGS gas sensors for demonstration of the MDC method, b) Sensors array responses in a plane defined by the first and second principal components.

The results of using the MDC methods for drift corrections are shown in Fig. 3. In Fig. 3 a) the corrected responses of array are shown. The correction with MDC algorithm was performed according to the following procedure. First, reference measurements were chosen (the initial values of sensor responses), then correction factors (the ratio of the sensor response after a series of measurements to the reference value) were estimated for a series of each 100 measurement points. When the drift occurred, the values of correction factors created a set of linearly changing values, on which the linear regression was estimated. The regression coefficients were used to correct all samples in a series of 100 points.

Fig 3 b) displays the results of correction in the plane defined by first and second principal components. The obtained results show that it was possible to move back

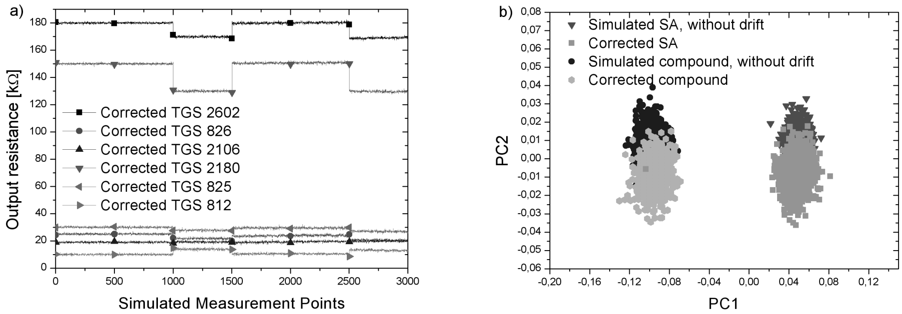

Fig. 3. a) Corrected responses using the MDC method, b) Results of individual sensor responses correction in the PCs defined plane.

the shifting clusters to the reference classes and avoid the classification errors which could possibly occur.

The second performed simulation case was prepared to show the results of using the CC method. The sensors responses with drift, and their representation in the PCs defined space is shown in Fig. 4. In this simulation case, the drift was generated after 1000 measurement points. The responses of array without drift are shown in Fig. 4 b) as red and blue clusters. The green and light blue point represent the responses with drifting signals. Also, the empty markers indicate measurements which were treated as reference samples to estimate the drift direction according to the CC procedure (values of the first PCA loading vector to be later removed from data which are corrected).

The results of using the Component Correction method on the simulated data are shown in Fig. 5. After using reference samples, based on which the drift direction was estimated, it was possible to successfully remove the negative effect of drifting sensor signals from the data. The corrected data was shifted back to the reference classes (signals without drift) which enabled correct classification using the original calibration model.

5. Conclusions

This work outlines the drift of sensor responses which is one of the most challenging problems in gas-analyzing systems. Two methods, MDC and CC, for drift counteraction were described and applied to the simulated gas sensors array responses. The results of usage of those methods have been shown. Both methods, in case of performed simulations, provided significant improvement of sensor responses long term stability. In the case of real-life systems, those relatively simple procedures seem to be efficient tools for mitigation the negative effect of drift phenomena and can provide improvement of such systems.

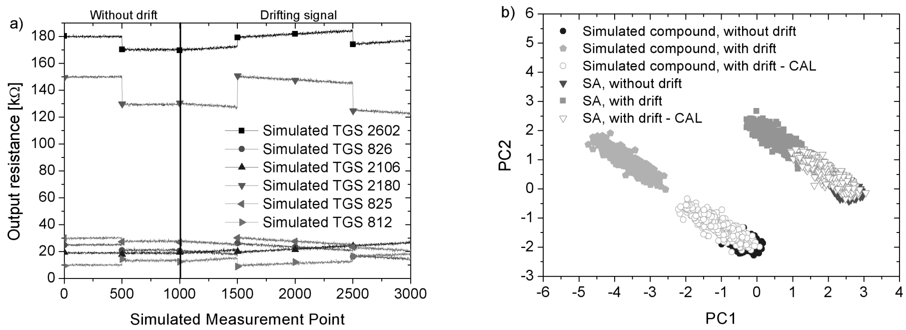

Fig. 4. a) Responses of six simulated TGS gas sensors for demonstration of the CC method, b) Sensors array responses in a plane defined by the first and second principal components.

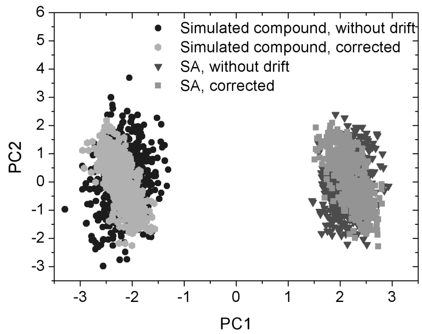

Fig. 5. Results of using the CC method on the sensor array responses.

References

Artursson, T., T. Ekloev, I. Lundstroem, P. Martensson, M. Sjoestroem and M. Holmberg (2000), ‘Drift correction for gas sensors using multivariate methods’, *Journal of Chemometrics* **Volume 14**, 711–723.

Di Carlo, S. and M. Falasconi (2012), *Drift Correction for Gas Chemical Sensors in Artificial Olfaction Systems: Techniques and Challenges*, InTech.

Haugen, J. E., O. Tomic and K. Kvall (2000), ‘A calibration method for handling the temporal drift of solid state gas sensors’, *Analytica Chimica Acta* pp. 23–39.

Holmberg, M. and T. Artursson (2003), *Drift Compensation, Standards, and Calibration Methods*, Wiley.

Scott, S. M., D. James and A. Zulfiqur (2007), ‘Data analysis for electronic nose systems’, *Microchimica Acta* pp. 183–207.

Wold, S., K. Esbensen and P. Geladi (1987), ‘Principal component analysis’, *Chemometrics Inltell. Lab. Syst.* **Volume 2**, 37–52.