Comparative Study of Drift Compensation Methods for Environmental Gas Sensors

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Abstract. Most drift compensation attempts in environmental gas sensors are only emphasize on the “already-known” drift-causing parameter (i.e., ambient temperature, relative humidity) in compensating the sensor drift. Less consideration is taken to another parameter (i.e., baseline responses) that might have affected indirectly with the promotion of drift-causing parameter variable (in this context, is ambient temperature variable). In this study, the “indirect” drift-causing parameter (drifted baseline responses) has been taken into consideration in compensating the sensor drift caused by ambient temperature variable, by means of a proposed drift compensation method (named as RT-method). The effectiveness of this method in its efficacy of compensating drift was analysed and compared with the common method that used the “already-known” drift-causing parameter (named as T-method), using drift reduction percentage. From the results analysis, the RT-method has outperformed T-method in the drift reduction percentage, with its ability to reduce drift up to 64% rather than the T-method which only able to reduce up to 45% for TGS2600 sensor. It has proven that the inclusion of drifted baseline responses into drift compensation attempt would resulted to an improved drift compensation efficiency.

1. Introduction

Volatile organic compounds (VOCs) can be used as a precursor for the increasing of ozone and particulate matter in tropospheric. The main source of VOC is emitted from vehicle, traffic flows and fuel transport. Many VOCs have toxic characteristics which not only give great influence on climatic change [1], but also deteriorate air quality and threaten human health (i.e., benzene could lead to carcinogenic, while toluene may cause vertigo symptoms; for long term cumulative effect on health conditions) [2]. Miniaturized-devices (namely gas sensors) have been developed for monitoring purposes which giving better option on low at cost, continuous monitoring, compact and portable [3-9]. However, the existing sensor designs have a drawback when signal response cannot be fully optimized due to its sensitivity to surrounding environmental variables (i.e., environmental temperature and relative humidity) that has caused drift-effects [10-16]. In this paper, the study was aimed to compensate the sensor’s signal drift using drift compensation model of T- and RT- methods. In compensating the signal drift, RT-method was emphasized on drifted baseline response utilization whereas T-method was used ambient temperature variable as compensating parameter.
2. Methodology

2.1. Data collection

Two Taguchi Gas Sensor (TGS2600 and TGS2602) sensors were used in this study and drifted responses have obtained under varied ambient temperature at 25, 30 and 35 °C with two different exposures; i) in exposure of clean air (baseline responses), and ii) in exposure of benzene at concentration of 0.5, 1, 5 and 10 ppm. Sensor resistance ($R_a$) was then calculated from the acquired responses ($V_{OUT}$) using equation:

$$R_a = \frac{v_c \times R_L}{V_{OUT}} - R_L$$  \hspace{1cm} (1)

where $V_c$ is the sensor’s circuit voltage and $R_L$ is the sensor’s load resistor. Since there are two types of exposure (in clean air and in benzene), therefore $R_a$ for these two exposures are denoted as $R_a$ (for exposure in clean air) and $R_g$ (for exposure in benzene).

The calculated $R_a$ and $R_g$ were then been pre-processed before further analysis can be proceed, in order to carefully select a number of parameter that are descriptive of the signal responses [17]. The pre-processing steps of relative baseline manipulation ($R_a/R_g$) and compression (using steady-state responses) were performed in order to retain the signal responses structure that carry relevant information (particularly information about the drift due to ambient temperature variable).

2.2. Drift Compensation

Linear regression model is used for the compensations of T- and RT- methods. The T-method is a one stage compensation method that compensates drift upon ambient temperature variable. Meanwhile, the RT-method include a two stages compensation method; which i) compensates drift upon drifted baseline response ($R_a$), and ii) compensates the compensated responses obtained from the first compensation stage ($R_g$-compensated) upon ambient temperature variable – as for final result standardisation, so that results for both T- and RT- methods are reflected into sensor responses that are unaffected with the change of ambient temperature values.

Both of these two compensation methods have taken sensor responses at ambient temperature of 25°C as the point of calibration to compensate the other responses that had been drifted at 30 and 35°C. The drifting model for both of these T- and RT- methods are as follows:

for T-method,

$$F = a + bT$$  \hspace{1cm} (2)

for RT-method (first compensation stage),

$$F = a + bR_a$$  \hspace{1cm} (3)

where $F$ is the feature of drifted sensor responses (uncompensated) denoted as $R_a/R_g$-UNCOMP, $a$ is constant, $b$ is coefficient of slope line obtained from the drifting model, $T$ is ambient temperature variable and $R_a$ is drifted baseline responses.

A new feature of sensor responses (compensated) was derived based on the coefficient of $b$ for each corresponding methods – $F_{T25}$ for T-method (compensated from ambient temperature variable) and $F_{Ra25}$ for first stage of RT-method (compensated from drifted baseline responses), respectively obtained using equation as follows;

$$F_{T25} = F - b(T - T_{25})$$  \hspace{1cm} (4)

$$F_{Ra25} = F - b(R_a - \bar{R}_{a25})$$  \hspace{1cm} (5)

where $T_{25}$ is the ambient temperature of 25°C, and $\bar{R}_{a25}$ is the mean value of drifted baseline response at 25°C.

The second compensation stage of RT-method was performed using the $R_{a25}$-compensated responses (obtained from the previous compensation stage) through model equation as follows:

$$F_{Ra25} = a + bT$$  \hspace{1cm} (6)

where $F_{Ra25}$ is the $R_{a25}$-compensated responses, $a$ is constant, $b$ is coefficient of slope line obtained from the model and $T$ is the ambient temperature variable.

The coefficient of $b$ was used in obtaining a new feature of sensor responses, which is $F_{RT25}$, compensated from the dependence of ambient temperature variable, $T$, using equation:

$$F_{RT25} = F - b(T - T_{25})$$  \hspace{1cm} (7)

where $T_{25}$ is the ambient temperature variable of 25°C.

From both of these T- and RT- compensation methods, the obtained $F_{T25}$ were the final results of compensated sensor responses for T-method compensation (denoted as $R_a/R_g$-T25COMP),
meanwhile the obtained $F_{RT25}$ were the final results of compensated sensor responses for RT-method compensation (denoted as $R_a/R_g$-RT25COMP).

2.3 Compensation comparison
The compensation efficiency for both methods was quantified using a variability measure of coefficient of variation (CV). CV is defined as the ratio of the standard deviation ($\sigma$) to the mean ($\mu$), showing the extent of drift in relation to the sensor response’s population as follows;

$$CV = \frac{\sigma}{\mu}$$  \hspace{1cm} (8)

Through this $CV$, the drift reduction percentage of compensated responses were measured using the equation:

$$CV_{\text{red\%}} = \left(\frac{CV_{\text{UNCOMP}} - CV_{\text{COMP}}}{CV_{\text{UNCOMP}}}\right) \times 100$$  \hspace{1cm} (9)

where $CV_{\text{red\%}}$ is the sought drift reduction percentage value, $CV_{\text{UNCOMP}}$ is the CV value of uncompensated sensor responses ($R_a/R_g$-UNCOMP), and $CV_{\text{COMP}}$ is the CV value of any compensated sensor responses ($R_a/R_g$-T25COMP or $R_a/R_g$-RT25COMP).

3. Results and Discussion
Fig. 1 shows the distribution of TGS2600 sensor responses before (UNCOMP) and after (T25COMP and RT25COMP) compensation based on the concentration of benzene exposure (0.5, 1, 5 and 10ppm).

![Figure 1. TGS2600 sensor responses distribution before (UNCOMP) and after (T25COMP and RT25COMP) compensation.](image)

From the figure, in graphs for UNCOMP, results show negatively correlated between the drifted sensor responses and ambient temperature variable. As this drift was compensated, the distribution of the resulted compensated responses for T25COMP and RT25COMP has improved to calibrate around the sensor responses at ambient temperature of 25°C (as the point of calibration).

For example, in graphs for T25COMP, since the compensation’s calibration point is based on ambient temperature variable at 25°C, thus the responses at 25°C were remain unchanged as its original UNCOMP responses, and responses at 30 and 35°C were compensated/calibrated to resemble this responses of 25°C. This compensation has resulted a “rotated” version of responses distribution (from the original UNCOMP) to be around the responses at 25°C (observed through the “rotated” trend line).
Meanwhile for RT25COMP, since the compensation was performed through two compensation stages, which main emphasize was given on the first one (compensation upon drifted baseline responses), the responses distribution can be seen differ from T25COMP. From this difference of responses distribution, obviously the span of compensated responses for RT25COMP has been reduced further than the T25COMP compensation (reduced variability). This drift reduction had been analyzed through the quantification of coefficient of variation (CV) value (as the form of variability or drift measure). Results of this drift reduction quantification are as shown in Table 1.

Table 1. Drift reduction percentage \( (CV_{\text{red}}\%) \) values for T25COMP and RT25COMP compensations.

| Benzene Concentration (ppm) | T25COMP \( (CV_{\text{red}}\%) \) | RT25COMP \( (CV_{\text{red}}\%) \) |
|----------------------------|----------------------------------|----------------------------------|
| 0.5 ppm                    | 22%                              | 58%                              |
| 1 ppm                      | 45%                              | 64%                              |
| 5 ppm                      | 28%                              | 37%                              |
| 10 ppm                     | 5%                               | 52%                              |

Table 1 shows the drift reduction percentage results for RT25COMP are much higher as compared to the drift reduction percentage by T25COMP. At the concentration of 0.5 ppm of benzene, the \( CV_{\text{red}}\% \) for RT25COMP compensated responses is 58%, which is higher than the \( CV_{\text{red}}\% \) for T25COMP compensated responses that is 22%. From the overall percentage result, has shown that the compensation using RT25COMP is able to reduce drift from the original UNCOMP responses with much higher degree than the compensation using T25COMP. This significant drift reduction ability of using RT25COMP from RT-method is congruent with the study in [18], in which utilization of baseline responses in compensating drift would results to a surprising drift-effects reduction. Thus, shows that RT-method is more effective in compensating drift compared to the compensation attempt using T-method.

4. Conclusion
The high degree of reduced drift in drift reduction percentage for RT-method indicates the role of baseline responses is significant in compensating the sensors drift. Thus, proves the inclusion of drifted baseline responses into drift compensation attempt able to give better solution to the drift issue in sensor responses, rather than using the “already-known” drift-causing parameter alone, as what commonly found in current practice. This improved compensation method would then contribute to enhanced prediction accuracy of gas concentration estimation in further gas sensing analysis.

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References
[1] Gómez M C, Durana N, Navazo M, Alonso L, Garcia J A & Ilardia J L 2004 Application of validation data tests from an on-line volatile organic compound analyser to the detection of air pollution episodes in urban areas. *Analytica Chimica Acta* **524**(1–2 SPEC. ISS.) 41–49
[2] Chen X, Zhang G & Chen H 2010 Controlling Strategies and Technologies of Volatile Organic Compounds Pollution in Interior Air of Cars 2010 International Conference on Digital Manufacturing & Automation 450–453
[3] Lee D D & Lee D S 2001 Environmental gas sensors *IEEE Sensors Journal* **1**(3) 214–224
[4] Tsujita W, Ishida H & Morizumi T 2004 Dynamic gas sensor network for air pollution monitoring and its auto-calibration *Proceedings of IEEE Sensors* 56–59
[5] Conrad T, Reimann P & Schütze A 2007 A hierarchical strategy for under-ground early fire detection based on a T-cycled semiconductor gas sensor *Proceedings of IEEE Sensors* (2) 1221–1224
[6] Mabrook M & Hawkins P 2001 A rapidly-responding sensor for benzene, methanol and ethanol vapours based on films of titanium dioxide dispersed in a polymer operating at room temperature *Sensors and Actuators B: Chemical* 75(3) 197–202

[7] Ren H 2001 Current Voltage Characteristics of a Semiconductor Metal Oxide Sensor (University of Maine)

[8] Tinoco A V 2006 Improving the performance of micro-machined metal oxide gas sensors: Ptitization of th temperature modulation mode via pseudo-random sequences (June)

[9] Ueno Y, Horiuchi T, Niwa O, Zhou H, Yamada T & Honma I 2003 Portable automatic BTX measurement system with microfluidic device using mesoporous silicate adsorbent with nano-sized pores 95 282–286

[10] Abidin M Z, Asmat A & Hamidon M N 2013 Identification of initial drift in semiconductor gas sensors caused by temperature variation *Proceedings of 2013 IEEE 9th International Colloquium on Signal Processing and its Applications* (Kuala Lumpur) 285–288

[11] Abidin M Z, Asmat A & Hamidon M N 2014 Temperature drift identification in semiconductor gas sensors *Proceedings of 2014 IEEE Conference on Systems, Process and Control* (Kuala Lumpur) 63-67

[12] Hossein-Babaei F & Ghafarinia V 2010 Compensation for the drift-like terms caused by environmental fluctuations in the responses of chemoresistive gas sensors *Sensors and Actuators B: Chemical* 143(2) 641–648

[13] Marco S & Gutierrez-Galvez A 2012 Signal and data processing for machine olfaction and chemical sensing: A review *IEEE Sensors Journal* 12(11) 3189–3214

[14] Vergara A, Vembu S, Ayhan T, Ryan M A, Homer M L & Huerta R 2012 Chemical gas sensor drift compensation using classifier ensembles *Sensors and Actuators B: Chemical* 166–167 320–329

[15] Wang C, Yin L, Zhang L, Xiang D & Gao R 2010 Metal oxide gas sensors: Sensitivity and influencing factors *Sensors* 10(3) 2088–2106

[16] Korotcenkov G & Cho B K 2011 Instability of metal oxide-based conductometric gas sensors and approaches to stability improvement (short survey) *Sensors and Actuators B: Chemical* 156(2) 527–538

[17] Gutierrez-Osuna R 2002 Pattern analysis for machine olfaction: A review *IEEE Sensors Journal* 2(3) 189–202

[18] Macias M, Agudo J, Manso A, Orellana C, Velasco H & Caballero R 2014 Improving Short Term Instability for Quantitative Analyses with Portable Electronic Noses *Sensors* 14(6) 10514–10526