Change detection in an array of MOX sensors

Sepideh Pashami, Achim J. Lilienthal and Marco Trincavelli
Centre for Applied Autonomous Sensor Systems, Örebro University, Örebro, SE - 70182, Sweden
Email: {sepideh.pashami, achim.lilienthal, marco.trincavelli} @oru.se
http://www.aass.oru.se/

***Abstract*—In this article we present an algorithm for online detection of change points in the response of an array of metal oxide (MOX) gas sensors deployed in an open sampling system. True change points occur due to changes in the emission modality of the gas source. The main challenge for change point detection in an open sampling system is the chaotic nature of gas dispersion, which causes fluctuations in the sensor response that are not related to changes in the gas source. These fluctuations should not be considered change points in the sensor response. The presented algorithm is derived from the well known Generalized Likelihood Ratio algorithm and it is used both on the output of a single sensor as well on the output of two or more sensors on the array. The algorithm is evaluated with an experimental setup where a gas source changes in intensity, compound, or mixture ratio. The performance measures considered are the detection rate, the number of false alarms and the delay of detection.**

I. Introduction

Change point detection algorithms that analyze the response of an array of gas sensors and detect a change in the exposure of the array to a gas mixture can bring a significant leap forward in the construction of systems for monitoring of hazardous or pollutant gaseous compounds in e.g. harbors [1] or landfills [2]. In such applications, gas sensors are often deployed in an open sampling system (OSS) since it is often crucial to provide quick detection and restriction in costs and payload pose stringent limitations on the hardware that can be considered. Moreover, it is often desirable to expose sensors directly to the environment to be analyzed since the dynamic response of the gas sensors contains crucial information on the gas plume and in particular on the location of the gas source [3]. However, the OSS configuration entails additional problems, mainly due to the slow dynamics of most gas sensing technologies compared to the fast fluctuations in the concentration profile to which the sensor are exposed. The fluctuations in the concentration profile are due to the mechanisms of gas dispersion, which, in natural environments characterized by a high Reynolds number, are dominated by turbulence and advection [4]. This results into a gas distribution which is characterized by a fine and unpredictable structure.

Up to now, most of the work with gas sensors in an OSS, without a sensing chamber that controls the exposure of the sensors to the gas and other variables like temperature and humidity, has been developed under simplified assumptions such as steady air flow and a gas source emitting a single compound with constant emission rate for the whole duration of the experiments. Unfortunately, these assumptions rarely hold in scenarios of interest for practical applications. In this work, in an attempt to move towards realistic scenarios, we deal with a single gas source that changes compound, intensity or mixture of compounds in the course of a single experiment. The problem we investigate is the detection of the changes in the exposure of an array of metal oxide (MOX) gas sensors due to changes in the activity of the gas source. MOX sensors are the most common in OSS [3], mainly because of their commercial availability and the high sensitivity to non-hazardous compounds like alcohols that facilitate experiments. However, MOX gas sensors are particularly slow and therefore seldom reach a steady state when used in an OSS. Therefore the problem of detecting points of exposure change is particularly hard since they have to be distinguished from fluctuations in the sensor response due to turbulent gas dispersion. We present an algorithm for change detection derived from the well known Generalized Likelihood Ratio algorithm [5] and we evaluate it using three performance measures, namely the detection rate, the false alarm rate, and the delay of detection.

The detection of changes in the activity of a gas source based on the response of an array of MOX gas sensors has, to the best of our knowledge, not been studied so far. Wang et al. [11] address anomaly detection in the response of a sensor network deployed in coal mines. They propose a Bayesian Network approach to identify events and focus on combination of sensor data. However, they neglect problems entailed with chemical sensing such as the cross correlation among the response of gas sensors of different type.

We can also relate the change point detection problem addressed in this paper to the analysis of multivariate time series. Change detection in multivariate time series has a wide range of applications such as quality control, segmentation of signals, monitoring of production processes or vehicles. Probably the simplest solution for change detection is detecting when the measurements fall out of a predefined range. This solution has been proposed for quality control applications [6]. Other techniques estimate change points by investigating the behaviour of the measurements of the time series before and after a hypothetical change point. The most common algorithms, inspired by frequentist inference, are the Generalized likelihood Ratio (GLR) test [5], the Marginalized Likelihood Ratio (MLR) [7] and the CUmulative SUM (CUSUM) algorithm [5]. If a prior on the time of the change point can be assumed, Bayesian inspired algorithm have also been proposed [8]. Also, change point detection algorithms inspired by machine learning approaches such as one class

Support Vector Machine [9] have been proposed.

Finally, the ability to detect changes in the activity of a distant gas source with an OSS can substantially improve algorithms previously proposed in literature, e.g. gas source localization [10].

The rest of this paper is organized as follows: Section II describes the experimental setup on which the algorithms are designed tested, Section III explains the change point detection algorithm, Section IV presents the results and, finally, Section V draws the conclusions and gives an outline of future works.

II. The Experimental Setup

We carried out the experiments in a $5m \times 5m \times 2m$ closed room with static sensors where an artificial airflow of approximately $0.05\ m/s$ is induced. The airflow is created using two arrays of four fans (standard microprocessor cooling fans), one placed on the floor and one on the wall. The gas source is an odour blender a device developed by Nakamoto et al. [12] that allows fast switches in between different mixtures of compounds with a variable concentration. The outlet of the olfactory blender is placed on the floor $0.5\ m$ upwind with respect to an array of 9 metal oxide gas sensors (Figaro TGS2600, TGS2602, TGS2611, TGS2620 and e2v MiCS2610, MiCS2710, MiCS5521, MiCS5121, MiCS5135). The airflow at the outlet of the odour blender is set to 1 l/min. The sensors are sampled at 4 Hz. Figure 1 shows a picture of the experimental setup.

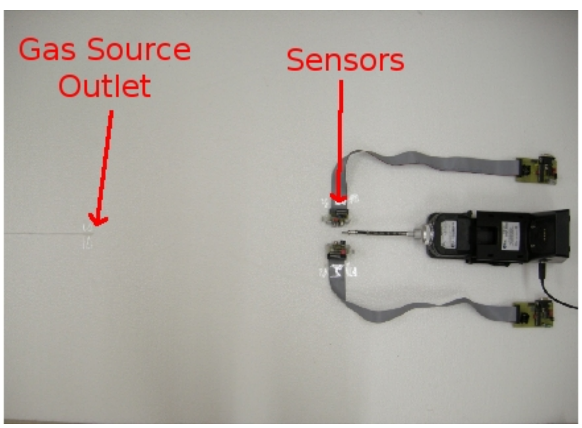


Fig. 1. Experimental setup with gas source and the sensor arrays used to detect changes.

The two compounds selected for these experiments are ethanol and 2-propanol. Both ethanol (molecular weight 46 g/mol) and 2-propanol (molecular weight 60 g/mol) are heavier than air (average molecular weight 29 g/mol), and therefore will tend to create a plume at the ground level. The two substances have a similar saturated vapor pressure, namely 5.8 kPa for ethanol and 4.2 kPa for 2-propanol, which means that they have a similar tendency to evaporate. Moreover MOX gas sensors have comparable sensitivity to the two substances. This is important in order to obtain similar sensor responses

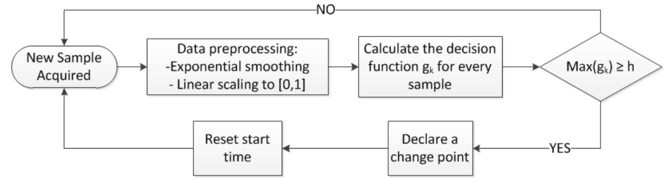


Fig. 3. Block diagram explaining the on-line GLR algorithm.

for both analytes thus avoiding to address a trivial instance of the change detection problem.

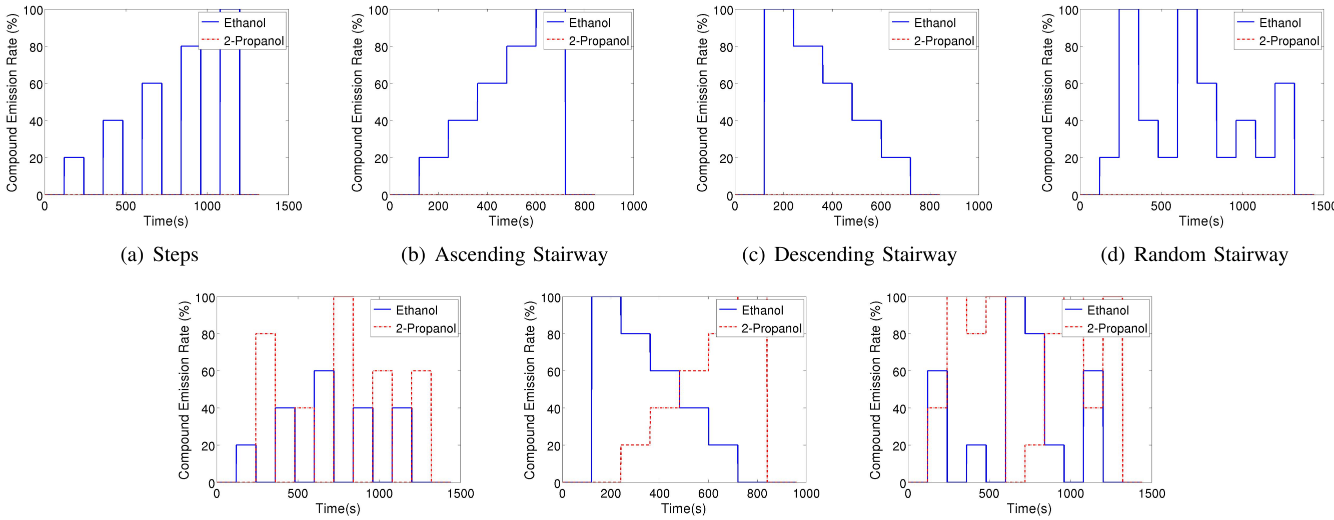
In order to create a database that allows to study the dynamic behaviour of the sensors when consecutively exposed to different analytes, seven different odour emitting strategies have been applied. In all the emitting strategies the gas source emits clean air for two minutes and the signal of sensors during this period is assumed as a baseline. Also, at the end of all the experiments the source emits clean air for 2 minutes. Figure 2 shows the intensity profile for the gas source in the various emission strategies. The control signal of the odour blender is used as a ground truth for the change point time. However, this control signal provides us the time in which the source changes the emission modality. In order to have the change point time at the sensors location we need to estimate the time the gas takes to travel from the gas source to the sensor location. change times at the source location, therefore, we need to calculate change times at the sensor location. Since the sensors are placed at $0.5\ m$ distance from the location of the source outlet and a steady air flow of $0.05\ m/s$ is induced, the delay time between change times at source and sensor location is estimated to be $10\ s$.

III. Change Point Detection Algorithm

The task of the change point detection algorithm is to identify changes in the exposure of the sensor array through the analysis of the multivariate time series constituted by the sensor measurements. In particular, in this work changes in the exposure are due to a change in the intensity of the gas source, a change in the chemical compound the gas sensor is exposed to, and a change in the gas mixture by analyzing the sequence of local measurements. No prior information is assumed about the position of change points. Besides, since no information about the length of the monitoring process is not available, an algorithm that process data on-line is chosen. Because of these reasons, we are using an adaptation of the well known Generalized Likelihood Ratio (GLR) algorithm [5]. The presented algorithm is schematically shown in Fig. 3. In the next sections the data preprocessing, the GLR algorithm and the performance measures used to evaluate the algorithms are described.

A. Data Preprocessing

Before running the GLR algorithm to detect change points the sensor measurements are preprocessed with an Exponential Moving Average (EMA) low pass filter [13] and normalized with a linear transformation in order to bring the value to



(a) Steps (b) Ascending Stairway (c) Descending Stairway (d) Random Stairway

(e) Random Switching (f) Mixture Stairway (g) Random Mixture

Fig. 2. Gas source emission strategies. Strategies (a)-(d) are displayed only for ethanol (they are repeated identically also with 2-propanol as target gas). For the randomized strategies, i.e. (d), (e), and (g), only one instance is displayed.

the $[0,1]$ interval. The cut-off frequency of the EMA filter is selected to be $0.44\ Hz$ which is higher than the one applied by the MOX sensors themselves. In this way this filter mainly removes the noise due to the electronics.

B. GLR Algorithm

Given the smoothed and normalized sensor response $\acute{s}_{1\ldots k}$ where k is the current time index, the GLR algorithm calculates the likelihood ratio between the hypotheses of having a change point at sample j versus the hypothesis of not having a change point:

$$\Lambda_j^k = \frac{\prod_{i=1}^{j-1} p_{\theta_0}(\acute{s}_i) \prod_{i=j}^{k} p_{\theta_1}(\acute{s}_i)}{\prod_{i=1}^{k} p_{\theta_0}(\acute{s}_i)} = \prod_{i=j}^{k} \frac{p_{\theta_1}(\acute{s}_i)}{p_{\theta_0}(\acute{s}_i)} \quad (1)$$

where the likelihoods are based on a parametric probability distribution p_θ function which is governed by a set of parameters θ. Since no prior information on the sensor noise is available, the most natural choice for p_θ is the Gaussian distribution, which is governed by two parameters, namely the mean and the variance. θ_0 denotes the mean/variance estimated using all samples in the time interval to be checked for change points. θ_1 denotes the mean/variance estimated using only the samples collected after sample j, which is the location of the hypothetical change point that have to be checked. For numerical reasons, it is more convenient to calculate the log-likelihood value S_j^k instead of the likelihood Λ_j^k itself:

$$S_j^k = \sup_{\theta_1} \sum_{i=j}^{k} \ln \frac{p_{\theta_1}(\acute{s}_i)}{p_{\theta_0}(\acute{s}_i)} \quad (2)$$

The decision function g_k is obtained by taking the maximum with respect to the possible change point time j:

$$g_k = \max_{i \le j \le k} S_j^k \quad (3)$$

If g_k is above a pre-selected threshold h, then a change-point is declared and the data collected before the change point are not considered any longer to detect new change points. In case of detected change point, k is the *alarm time*.

C. Performance Measures

In order to define the performance measures we first define the concepts of true alarm, false alarm, and delay of detection. A *true alarm* is defined as the first alarm after a change point. Any other alarm coming after the true alarm and before the next change point is defined as a *false alarm*. The *delay of detection* is defined as the difference between the alarm time of a true alarm and the time of the change point.

The first performance measure we consider is the true alarm ratio (TAR) which is given by the total number of true alarm divided by the number of change points. Clearly, the value of this performance measure is bounded between 0 and 1. The second performance measure is the false alarm ratio (FAR) which is calculated as the total number of false alarms divided by the number of change points. Notice that this performance measure is unbounded above. The third performance measure is the mean delay of detection (MDD) and is defined as the average of the delay of detection.

IV. Results

As an illustrative example of the kind of signals we are dealing with in this work, Figure 4 displays the sensor response obtained for one experiment. The true alarm ratio (TAR), mean delay of detection (MDD) and selected thresholds when the maximum false alarm ratio (FAR) is set to 0.1 are reported in Table I, Table II and Table III respectively. According to Table I, the sensor achieving the overall best performance is the MiCS 2710 that achieves a true alarm ratio of 0.90. More specifically, the MiCS 2710 is the best sensor for detecting

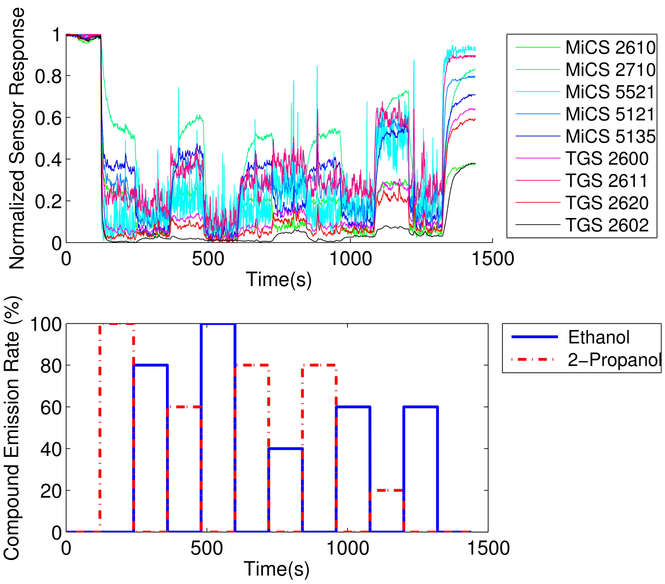


Fig. 4. Sensor response obtained for the Random steps emission strategy. In these experiments the gas source emits ethanol and 2-propanol in alternation with random intensity. The sensor response is defined as the instantaneous sensor resistance divided by the value of the resistance measured during the baseline acquisition.

TABLE I
TRUE ALARM RATIO (TAR),
FALSE ALARM RATIO (FAR) SET TO 0.1

Model	**All**	**Change Concentration**	**Change Compound**	**Change Mixture**
TGS 2600	0.73	0.86	0.77	0.47
TGS 2602	0.73	0.87	0.68	0.51
TGS 2611	0.49	0.64	0.45	0.25
TGS 2620	0.66	0.83	0.70	0.34
MiCS 2610	0.83	0.81	1.00	0.77
MiCS 2710	0.90	0.90	0.95	0.86
MiCS 5521	0.55	0.72	0.52	0.27
MiCS 5121	0.74	0.78	0.84	0.59
MiCS 5135	0.85	0.82	0.99	0.80

changes in concentration and mixture, while for what concerns changes in compound the MiCS 2710 is the third best after the MiCS 2610 and MiCS 5135. Table IV provides further details presenting the best sensor for each kind of change point and each of the two compounds considered. The MiCS 2710 gives best performance as a single sensor in 14 out of 14 experiments that involve only changes in concentration and the compound is ethanol. The TGS 2600 and MiCS 5135 instead prove best for detecting changes in concentration of 2-propanol. Changes in compound are detected best by the MiCS 2610, while sensor MiCS 2710 proves best in detecting changes in mixture. However, considering the delay of detection reported in Table II we can observe that the MiCS 2710 has a high detection delay, while sensors MiCS 2610 and MiCS 5521 prove to be relatively fast. Probably the sensors providing the best trade-off between the performance measures are the MiCS 5135 and MiCS 2610 sensors.

TABLE II
MEAN DELAY OF DETECTION (MDD) IN SECONDS,
FALSE ALARM RATIO (FAR) SET TO 0.1

Model	**All**	**Change Concentration**	**Change Compound**	**Change Mixture**
TGS 2600	56.5	52.3	51.0	67.1
TGS 2602	69.9	70.5	72.2	67.5
TGS 2611	79.5	84.4	91.8	63.1
TGS 2620	56.2	54.8	59.2	56.6
MiCS 2610	48.7	51.7	40.8	48.4
MiCS 2710	70.1	71.0	65.7	71.1
MiCS 5521	52.5	55.7	53.5	46.3
MiCS 5121	55.6	53.5	55.0	59.8
MiCS 5135	53.3	53.5	48.6	55.9

TABLE III
SELECTED THRESHOLD WITH FALSE ALARM RATIO (FAR) SET TO 0.1

Model	**Threshold**
TGS 2600	355
TGS 2602	455
TGS 2611	660
TGS 2620	390
MiCS 2610	350
MiCS 2710	400
MiCS 5521	385
MiCS 5121	390
MiCS 5135	375

V. CONCLUSION

This paper has investigated for the first time the problem of change detection for an array of MOX gas sensors. Changes in the exposure of the gas sensors are caused by changes in the emission modality of the gas source. The gas source produces changes in gas concentration, chemical compound or mixture ratio between two compounds. A change point detection algorithm based on the Generalized Likelihood Ratio algorithm has

TABLE IV
BEST SENSORS CHOSEN BASED ON TRUE ALARM RATIO (TAR) FOR THE DIFFERENT GAS SOURCE EMISSION STRATEGIES,
FALSE ALARM RATIO (FAR) SET TO 0.1

<table>
<tr><th>Category</th><th>Experiments</th><th>Ethanol</th><th>2-Propanol</th></tr>
<tr><td rowspan="4">Change in Concentration</td><td>Steps</td><td>All Sensors</td><td>All Sensors Except TGS 2611</td></tr>
<tr><td>Ascending Stairway</td><td>TGS 2600
MiCS 2710</td><td>TGS 2600</td></tr>
<tr><td>Descending Stairway</td><td>MiCS 2710</td><td>MiCS 5135</td></tr>
<tr><td>Random Stairway</td><td>MiCS 2710</td><td>TGS 2600</td></tr>
<tr><td>Change in Compound</td><td>Random Steps</td><td colspan="2">MiCS 2610</td></tr>
<tr><td rowspan="2">Change in Mixture</td><td>Mixture Stairway</td><td colspan="2">MiCS 2710</td></tr>
<tr><td>Random Mixture</td><td colspan="2">MiCS 2710</td></tr>
</table>

been proposed. The algorithm has been evaluated with respect to three performance measures. Future improvements to the results presented here include the extension of the proposed algorithm to consider the response of the sensor array as a multivariate time series instead of considering the sensors individually. This would also open the path for development of algorithm for selecting the most appropriate sensors to include in the sensor array. Further future developments will also include testing the proposed algorithms under conditions that are to be expected for real applications, for example when the sensor array is mounted on a mobile robot or when it is deployed in an outdoor uncontrolled environment with typically stronger airflow and larger turbulence levels. An example of a scenario where it can be very interesting to test the change point algorithms in the future is the Air Quality Egg project for monitoring pollution in towns [14].

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