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Improving Calibration of Chemical Gas Sensors for Fire Detection Using Small Scale Setups †

Ana Solórzano [1,2], Jordi Fonollosa [1,2,*] and Santiago Marco [1,2]

1 Department of Engineering Electronics, Universitat de Barcelona, Barcelona 08028, Spain; asolorzano@ibecbarcelona.eu (A.S.); smarco@ibecbarcelona.eu (S.M.)
2 Institute for Bioengineering of Catalonia (IBEC), The Barcelona Institute of Science and Technology, Barcelona 08028, Spain
* Correspondence: jfonollosa@ibecbarcelona.eu; Tel.: +34-934-031-118
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Abstract: Chemical sensing may be better suited than conventional smoke-based detectors for the detection of certain type of fires, in particular in fires where smoke appears after gas emissions. However, chemical-based systems also respond to non-fire scenarios that also release volatiles. For this reason, discrimination models need to be trained under different fire and non-fire scenarios. This is usually performed in standard fire rooms, the access to which is very costly. In this work, we present a calibration model combining experiments from standard fire room and small-scale setup. Results show that the use of small-scale setup experiments improve the performance of the system.

Keywords: fire detector; multisensor system; calibration model; gas sensor array; machine olfaction; fire alarm

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1. Introduction

For some type of fires, volatiles are released before smoke [1]. Hence, fire detectors based on chemical sensing could provide a faster fire alarm than smoke-based detection systems [2]. The challenge, however, is the large number of situations (nuisances) that also generate volatiles and that may lead to false alarms [3–4]. In this way, chemical sensing systems for fire detection rely heavily on machine learning, signal processing and pattern recognition techniques to provide a reliable fire prediction [5–7]. To develop robust and reliable algorithms for fire detection, calibration and test datasets that include different fire types and nuisances experiments are fundamental [8].

The systems used to provide fire alarms should be tested in standard rooms. Chemical systems for fire detection also need to be exposed to the fire standard conditions. However, the availability of standard fire rooms to perform experiments is limited and expensive. For this reason, it would be desirable the acquisition of data at smaller scale setups that can be used in combination of data acquired at standard fire rooms to extend, at a moderate cost, the calibration dataset.

In this work, we present a calibration methodology for fire detection based on a Partial Least Squares Discriminant Analysis (PLS-DA). The model was trained using the combination of data experiments from standard fire room and data experiments from small-scale setup.

2. Experimental

2.1. Sensor Board

We built a multi-sensor system composed of a PID Sensor (PID-A1, Alphasense), a NDIR CO_2 sensor (IRC-AT, Alphasense), a CO electrochemical sensor (CO-B4, Alphasense) and 8-MOX sensors

(AS-MLK, AS-MLC, AS-MLX, AS-MLN; provided by AMS, two units of each, at 337 °C and 436 °C). Signals were acquired and stored locally at a sampling frequency of 10 Hz using a low-cost general-purpose microcontroller coupled to the required signal conditioning electronics.

2.2. Datasets

To assess this methodology we used two different datasets; (i) Large-scale and (ii) Small-scale dataset. To collect the first dataset, the sensing system was placed in the celling of a standard fire room while several experiments of fires and nuisance were performed.

The large-scale dataset includes open and smoldering fire experiments described in the EN-54 norm, other smoldering fire types and nuisance scenarios. Specifically, we performed two repetitions of: TF2 (smoldering), electrical fire (smoldering), PVC Fire (smoldering), PET Fire (smoldering), cables fire (smoldering), TF3 fire (smoldering), TF4 (open) and TF6 (open). The nuisance scenarios selected were based on the presentation of different products: air freshener, ethanol (96% purity), turpentine, vinegar, and gasoline. The total number of experiments included in the large-scale dataset is 25.

The small-scale experiments were performed in a 272-L chamber. Small-scale dataset includes: 4 repetitions of electrical fire, reduced TF2 and reduced TF3, and several nuisance scenarios: boiling water, air freshener, ethanol, rising temperature, and two commercial cleaning products (vinegar and floor cleaner). The total number of experiments included in the small-scale dataset is 32. The sensor array detects volatiles released in fire and nuisance experiments performed in both scenarios (small and large), though, signatures of fire and nuisances are different due to the different dimensions (Figure 1).

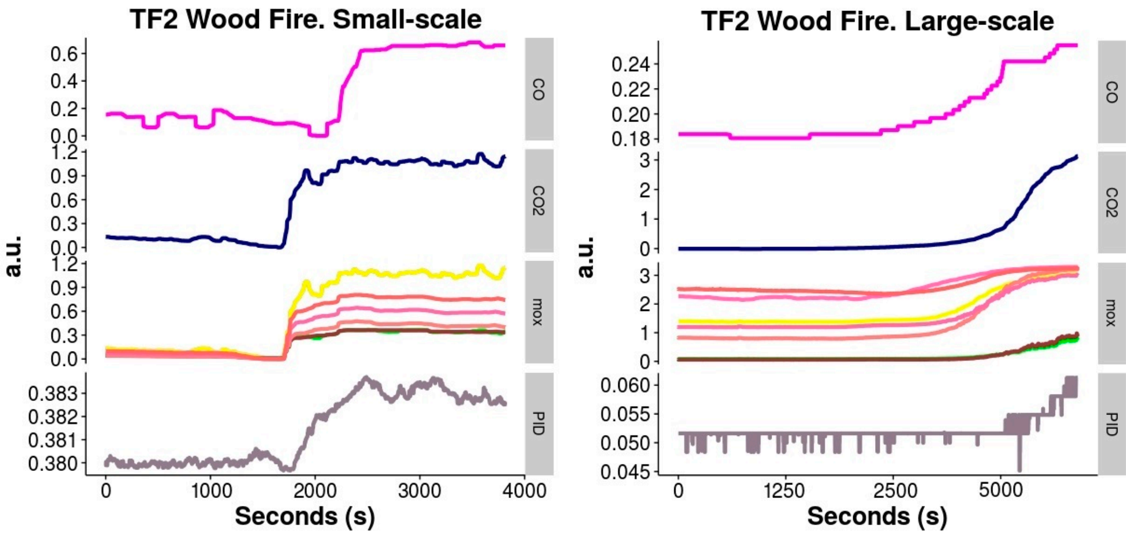

Figure 1. Signals captured for a TF3 experiment (smoldering cotton fire) in the small-scale set up (left) and in the fire room (right). Sensors detect volatiles released during the experiments, however, their reaction is different due to (mostly) the dimensions of the standard fire room.

3. Methods and Results

The prediction models are based on Partial Least Squares Discriminant Analysis (PLS-DA). A double cross validation methodology was implemented. Internal validation was used to optimize the parameters of the model and external validation was used to assess the performance of the classifier. The first model was trained using repetitions of the large-scale dataset and is able to classify all the fire experiments. However, the model confused 8 nuisance experiments with fire, resulting in false alarms. Table 1 shows the confusion matrix after 12 iterations.

A second model was built adding to the calibration set the data captured in the small-scale setup. Along the 12 cross validation iterations, models classified 100% of the nuisance experiments and confused only the PVC fire experiment. Table 2 shows the confusion matrix

Table 1. Confusion matrix of the model when it is trained with data from standard fire room only. Although the system is able to detect all the fires, the number of false positive is unacceptable.

	Fire Alarm	No Fire Alarm
Fire	15	0
Nuisance	8	2

Table 2. Confusion matrix of the model when it is trained with data from standard fire room and data acquired at smaller-scale setup. Additional measurements help to adjust alarm levels so none of the nuisances generates a false alarm.

	Fire Alarm	No Fire Alarm
Fire	14	1
Nuisance	0	10

4. Conclusions

PLS-DA models were built to classify different fire scenarios and discriminate non-fire scenarios that may produce false alarms. Models that only used large-scale datasets in the calibration set showed poor specificity. Nevertheless, results indicated that the model trained with the combination of the small-scale and large-scale datasets is capable of rejecting all the nuisances and detecting most of the fires. Further work is needed to keep sensitivity to fires at higher levels when false alarm immunity is increased.

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Conflicts of Interest: Authors declare no conflict of interest.

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