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FIRE DETECTION USING A GAS SENSOR ARRAY WITH SENSOR FUSION ALGORITHMS

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ABSTRACT

Conventional fire alarms are based on smoke detection. Nevertheless, in some fire scenarios volatiles are released before smoke. Fire detectors based only on chemical sensors have already been proposed as they may provide faster response, but they are still prone to false alarms in the presence of nuisances. These systems rely heavily on pattern recognition techniques to discriminate fires from nuisances. In this context, it is important to test the systems according to international standards for fires and testing the system against a diversity of nuisances. In this work, we investigate the behavior of a gas sensor array coupled to sensor fusion algorithms for fire detection when exposed to standardized fires and several nuisances. Results confirmed the ability to detect fires (97% Sensitivity), although the system still produces a significant rate of false alarms (35%) for nuisances not presented in the training set.

Index Terms— Fire alarm, Sensor fusion, Gas sensor array, Machine Olfaction, Multisensor system.

1. INTRODUCTION

Conventional fire alarms based on smoke detection do not trigger the alarm until smoke or combustion particles are produced in fires. Nevertheless, in certain types of fires, volatiles appear before smoke. Actually, most of the fatalities related to fires in buildings are caused by toxic emissions that conventional fire alarms are unable to detect [1]. Chemical gas sensors are able to detect gas emissions produced in fires and, therefore, could provide faster response and detect the emission of toxic compounds.

For many years fire detectors based on chemical sensors have been explored. In the decade of the 80's, Pfister et al. [2] studied the sensitivity of different chemical sensor technologies to detect volatiles released in fires. Their work confirmed the feasibility of gas sensors to detect fires.

However, gas sensors also respond to many other stimuli that may lead to false alarms. To obtain reliable fire detection one needs to counteract cross-sensitivity of sensors to environmental conditions and nuisances. This can be achieved by taking advantage of the different chemical signatures that fires and nuisance induce to the sensors and making use of machine learning algorithms [3-5].

Different strategies have been proposed to build classification models to detect fires and reject nuisances. For example, a reference work was published by Rose-Pehrson et al. [6]. They compared responses of 17 different sensor technologies to 24 fires and 12 nuisances. Additionally, they developed pattern recognition algorithms based on probabilistic networks that reached 94% of correct classification for fires. A series of interesting works were developed by researches of Saarland University [7,8]. They designed a sensing system for fire detection in coal mines. They proposed a hierarchical strategy based on Linear Discriminant Analysis (LDA) to discriminate fires from non-fire scenarios. Moreover, authors analyzed differences between signals taken in real conditions and signals from laboratory conditions.

Nevertheless, since developed algorithms are data-driven, it is of utmost importance the calibration/test datasets. To build reliable systems large number of conditions (fire and nuisances) need to be presented to the detector. In view of system commercialization, it needs to be tested under standardized conditions. However, most of the previously published research does not use standard fire rooms due to the high associated costs of generating many conditions in large test rooms. Additionally, this work targets the detection of fires originating from overheated electronics and connections. Today there is large interest in those type of fires due to the increasing number of data centers spread all over the globe. Here, we present a fire detector that integrates several sensing technologies coupled with a Pattern Recognition System based on Partial Least Squares Discriminant Analysis for the classification of fires and nuisances.

2. FIRE DETECTOR AND EXPERIMENTS

We developed a gas sensor array for fire detection combining several sensing technologies. The sensors included in the system were: *8 AMS MOX sensors (MLX (2), MLC (2), MLV (2), and MLN (2)), a PID alphasense sensor (PID-A1), NDIR CO_2 alphasense sensor (NDIR-A1), an Electrochemical CO alphasense sensor (CO-B4), and Humidity and Temperature sensirion sensor (SHT 75)*. Signal conditioning circuitry was designed specifically for each sensor. Analog sensor signals were acquired using an Arduino DUE board at 10 Hz.

Our prototype was placed in the ceiling of a standard fire room, at the facilities that Minimax has in Germany, in which all the experiments were performed. The algorithm was trained with six different types of fires experiments and six different types of nuisances. Additionally, models were also evaluated with nuisances not presented during training to test the robustness of the system.

Specifically, we performed *TF2* and *TF3* standard fires (according to EN-54). Other smoldering fires were also generated in the standard fire room, namely *Electrical Fire, PVC Fire, PET Fire, and Cables Fire*. In order to generate scenarios that may result in false positive alarms different nuisance experiments were also performed: *Window Cleaning, Air Freshener, Gasoline, Turpentine, Ethanol, and Vinegar*. The complete dataset is composed by 19 fires and nuisance experiments, with repetitions of some scenarios (see Table 1).

Table 1 Experiments performed in the standard fire room in the period of 5 days, with the number of repetitions for each scenario.

TYPE	**EXPERIMENT**	**MATERIAL**	**Rep.**
Fire	TF2	Wood	2
Fire	TF3	Cotton	1
Fire	Electrical Fire	Electronic Components	2
Fire	PVC	PVC	2
Fire	PET	PET	2
Fire	Cables Fire	Electrical Cable	2
Nuisance	Window Cleaning	Cleaning Product	1
Nuisance	Air Freshener	Air Freshener	2
Nuisance	Gasoline	Gasoline for cleaning	1
Nuisance	Turpentine	Turpentine	1
Nuisance	Ethanol	Ethanol	2
Nuisance	Vinegar	Vinegar	1

3. METHODS

3.1 Pre-processing and feature extraction

In order to improve the performance of the classification algorithms a pre-processing signal stage was performed. The NDIR sensor active signal was divided by the reference channel. The conductance of the eight MOX sensors was considered. Feature extraction consisted in dividing the data into segments of 1 second. The extracted feature corresponds to the mean of 10 data points (10 Hz of sample frequency) included in each segment.

Figure 1 shows an example of signals captured during a "TF2" fire and Ethanol experiments. It confirms the challenge of rejecting nuisances. Although sensors respond

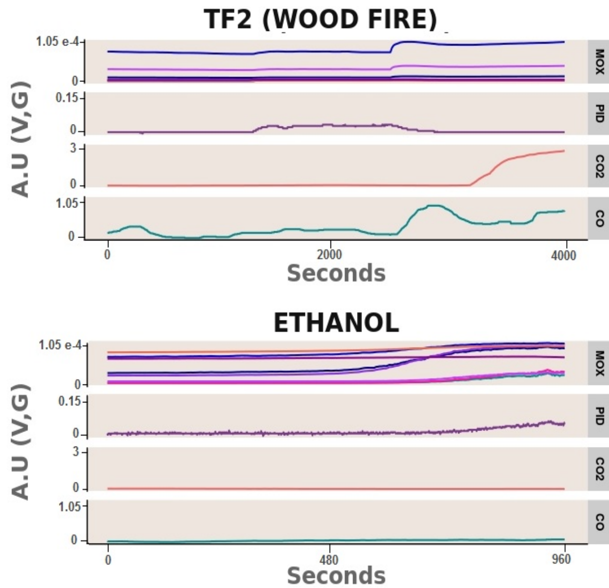

Figure 1. Signals captured for TF2 and ethanol experiments. The sensor array detects volatiles released during "TF2" fire experiment (Top). Sensors also react to the ethanol (Bottom).

to combustion products, they do so as well for non-fire scenarios (in particular, MOX sensors for the considered example). Consequently, to discriminate fires from nuisances pattern recognition techniques are needed.

3.2 Fire detector algorithm

To obtain reliable fire predictor, algorithms were trained with fire and nuisance experiments in order to capture their specific signatures. Additionally, models were tested with nuisances not presented in calibration in order to explore the robustness of the model against unseen nuisances.

Partial Least Squares Discriminant Analysis (PLS-DA) has been used as classification model. To prevent overfitting a double cross validation methodology was considered (CV) [13]. Internal validation was performed to optimize the number of latent variables (LV) of the PLS-DA model. The dataset which contains 19 experiments (11 fire and 8 nuisance experiments) was divided in two sets randomly: Training and Test. Training set consisted in 7 fire and 5 nuisance experiments. Test set contained 4 fires and 3 nuisance experiments. Internal validation was used to select the optimal number of latent variables according to classification rate obtained (4 fires and 3 nuisances to build the model and 3 fires and 2 nuisances to evaluate the classification rate, with 20 random data partitioning). After selecting the final model its performance is evaluated in external validation with the 7 experiments of the Test set. This procedure was repeated 20 times with new random dataset partitioning.

4. RESULTS

Classification models are capable to separate partially fires from nuisances. Figure 2 shows calibration and validation PLS-DA scores for one of the iterations colored according to fire / non-fire predictions. Calibration and validation samples follow similar distribution, resulting, thereby in a robust model for discriminating fires from nuisances. After evaluating the 20 repetitions, fires were classified correctly 97%. Nerveless, the main challenge is to achieve the fewer number of false positives when validating with types of nuisances not presented during calibration, as models present 37% of false alarms. A permutation test indicates the statistical significance of the results in all the models, the p-value computed is 0.0001 and finally a 0.8 of area under the curve ROC (AUC) was obtained.

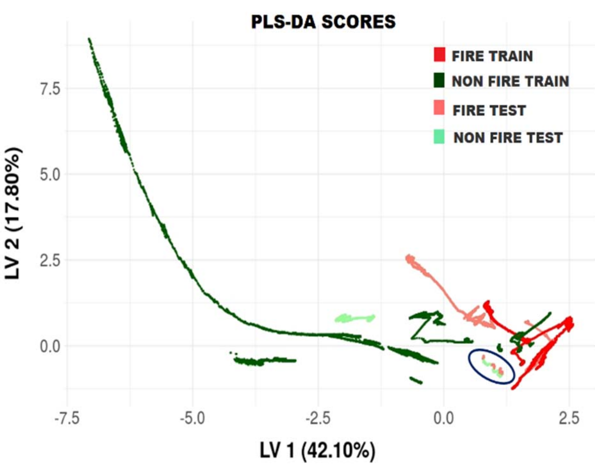

Figure 2 Calibration and validation PLS-DA scores projection. Scores are colored according to predicted labels. Blue circle highlights the confusion region.

5. CONCLUSIONS

The combination of gas sensor matrices and pattern recognition techniques provides high scores of classification rate. The presented models are able to detect fire and trigger fire alarm accordingly. However, in some cases when models are evaluated with nuisances not presented in calibration, false positives were produced. To reduce the ratio of false positives, repetitions of the nuisance experiments are required. Even so, models are capable to discriminate 63% of the nuisances scenarios not presented in the training set. In summary, the proposed fire detector based on chemical sensors coupled to pattern recognition techniques provides reliable predictions of fires while nuisance immunity still needs to be improved further.

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