

Is the initial response of gas sensors enough for gas recognition?

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Summary:

This work examines whether early-response features of metal-oxide (MOX) gas sensors enable reliable gas identification without waiting for signal stabilization. Four features are evaluated, the derivative (Dt), relative response (Rs), and area under the curve (AUC), including a truncated version (AUC-20s) using only the first 20 seconds. Using a multilayer perceptron and intrinsic dimensionality analysis on an open dataset of 11 gases across three sensor positions, results show that early features can match or outperform Rs, with AUC-20s performing best for real-time applications.

Keywords: metal-oxide sensors, gas identification, real-time monitoring, feature extraction, intrinsic dimensionality

Introduction

Gas sensing using metal-oxide semiconducting (MOX) sensors has gained traction due to their cost-effectiveness. Although they are a non-selective type of sensor, an array of different MOX sensors can match the performance of more costly selective sensors, when paired with a machine learning post-processing. However, calibration models typically rely on the stable sensor response relative to a baseline resistance, which is impractical for real-time monitoring. In this work, we investigate whether early-response features of MOX sensors, computable within the first few seconds of gas exposure, can support reliable gas identification. We compare the sensor derivative (Dt) against the relative response (Rs), the area under the curve (AUC), and a truncated variant (AUC-20s).

Methodology

As observed in previous studies, Dt can provide significant information for gas identification [1], [2]. To check if this feature is sufficient to recognize a target gas with similar performance to reference methods (Rs), the gold standard for gas sensing, and AUC, we perform the following procedure: (i) From the raw sensor response curves, extract 4 datasets, corresponding to their respective features: Dt, Rs, AUC, and AUC-20s; (ii) Perform a k-fold cross validation to evaluate the average accuracy of each dataset on a fixed model architecture. Here, $k = 10$; (iii) Perform an information content analysis of each dataset.

To compute Dt, the raw sensor response is truncated between the moment of gas injection and Δ samples after injection. The discrete derivative is then computed as:

$$dt[n] = s[n] - s[n - 1]$$

where $s[n - 1]$ and $s[n]$ are consecutive measurements at time indices $n-1$ and n , respectively, across the D sensors in the array. The resulting feature is the average value of dt per sensor. For the tests performed in this work, $\Delta = 20$ samples.

Rs is computed from each raw sensor response by extracting R_0 , the sensor resistance at the moment of gas injection, and R_g , the resistance at the end of the exposure period. The relative response is then computed as:

$$R_s = \begin{cases} (R_g - R_0)/R_0, & R_g \geq R_0 \\ (R_0 - R_g)/R_g, & R_g < R_0 \end{cases}$$

Finally, AUC is computed by the sum of measurements during an injection. For each d sensor:

$$AUC_d = \sum_{n=0}^N s_d[n]$$

where $n=0$ corresponds to the injection time and $n=N$ to the end of the exposure period. A truncated variant, AUC-20s, is also explored, where N is limited to the first 20 seconds of injection.

Experiments

Tests were performed using open dataset collected in [3]. For this work, the details that matter are that, in total 11 target gases are tested, with

a sampling period of 1 s, and measured by 8 individual commercially available sensors. The experimental protocol used to extract the data is as follows: (a) 20 s of clean air; (b) 3 minutes of target gas exposure; (c) 3 minutes of purging with clean air. Sensors are tested in several positions in relation to the gas source¹: P1, P3 and P4 (according to Figure 2 from the reference), under the assumption that performance degrades with increasing distance from the source. The selected sensing array is consistently the one located at the center of the chamber.

Gas classification was performed using a simple multilayer perceptron (MLP), with 7 neurons in the input layer (one for each sensor²), followed by a hidden layer of 15 neurons with a sigmoidal activation function. The output layer consists of 11 neurons (corresponding to the 11 target gases) and uses a softmax activation function to estimate valid class probability distributions. Input data were normalized prior to training and testing. The model was trained using the Adam optimizer with a fixed learning rate of 0.01, over 100 epochs with a batch size of 50. Total number of samples in each dataset was 3075.

An information content analysis was also performed by estimating the intrinsic dimensionality (ID) of the resulting datasets using the multiscale approach developed in [4].

Results and discussion

A summary of the classification results per feature and per position is shown in Table 1. While the AUC is computed during the whole injection period, AUC-20s considers only the first 20 seconds of injection, in the same way as Dt. Even with this limitation, AUC-20s still manages to outperform both Rs and Dt, making it the optimal choice within the tested features for gas classification task. This is especially true for real-time monitoring, since only the initial 11% of the exposure time results more effective than Rs, measured on the whole exposure time.

A summary of the information content analysis is provided in Table 2. It becomes clear that ID for AUC is in general higher, representing a higher complexity of the data, which may be advantageous for the classifier, as reflected in the higher accuracy results³.

Another interesting result from this analysis comes from the comparable ID of Dt and Rs. This indicates that the complexity of the resulting datasets is almost identical and likely to show

even closer results by selecting another classifier. Further study is still required on this point.

Table 1. Summary of gas classification accuracy per feature and per position.

Feature	Position		
	P1	P3	P4
Dt	94.01 ± 1.37 %	92.74 ± 1.59 %	89.75 ± 2.17 %
Rs	94.34 ± 1.61 %	94.08 ± 1.75 %	90.40 ± 1.70 %
AUC	98.66 ± 0.86 %	98.60 ± 0.98 %	97.39 ± 1.14 %
AUC-20s	95.93 ± 1.33 %	95.93 ± 1.54 %	93.46 ± 1.13 %

Table 2. Summary of intrinsic dimensionality (ID) estimation of the resulting datasets.

Feature	Position		
	P1	P3	P4
Dt	1.74	1.52	1.55
Rs	1.73	1.57	1.56
AUC	1.93	2.04	2.13
AUC-20s	2.20	2.11	2.22

Conclusions

In this work, we investigated whether early-response features of MOX gas sensors are sufficient for reliable gas identification. Results show that the sensor derivative (Dt), computed from only the first 20 seconds of exposure, achieves classification accuracy comparable to the standard relative response (Rs), suggesting that the initial transient response carries enough discriminative information for gas recognition. Furthermore, AUC-20s outperforms both Dt and Rs across all tested positions, making it a strong candidate for real-time gas monitoring applications. The information content analysis corroborates these findings, showing that AUC-based features present higher intrinsic dimensionality, indicating a higher level of complexity provided by the feature, which appears to be exploited by the classifier to achieve better performance.

References

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¹P2 was removed from the testing due to lack of data.

²TGS 2611 was removed from analysis due to scaling issues.

³High ID alone does not imply high classification accuracy, but it contributes to estimating mutual information between

observations and the gas class. Results in this study suggest that higher ID increases the information available about the class, warranting further research.