Multi-Gas Detection Using Sensor Fusion Technology

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***Abstract*—The accurate identification and quantification of multiple gases in complex environments is critical for industrial safety, environmental monitoring, and medical diagnostics. Traditional single-sensor approaches often suffer from cross- sensitivity, drift, and limited selectivity. This paper presents a novel multi-gas detection system based on sensor fusion technology that integrates an array of heterogeneous gas sensors metal oxide (MOX), electrochemical (EC), and non-dispersive infrared (NDIR)with a multi-stage data fusion architecture. The proposed system employs a hybrid fusion framework comprising a Kalman filter for signal-level denoising, a support vector machine (SVM) for classification, and an artificial neural network (ANN) for concentration estimation. Experimental results for a target gas set including methane (CH4), carbon monoxide (CO), and nitrogen dioxide (NO2) demonstrate that the fusion approach achieves a classification accuracy of 98.4% and a mean absolute error (MAE) of 1.2 ppm for concentration estimation, significantly outperforming individual sensor modalities. The system's robust- ness against sensor drift and environmental interference is also validated.**

***Index Terms*—Sensor fusion, multi-gas detection, metal-oxide sensor, electrochemical sensor, NDIR, machine learning, Kalman filter, artificial neural network.**

I. INTRODUCTION

The reliable detection of hazardous and environmentally relevant gases is a cornerstone of modern safety and monitoring systems [1]. Applications range from leak detection in industrial plants to indoor air quality management and non-invasive disease diagnosis through breath analysis. However, the development of a compact, selective, and accurate multi-gas detection system remains a significant challenge.

Single gas sensors, such as Metal-Oxide-Semiconductor (MOS) sensors, offer high sensitivity and low cost but suffer from poor selectivity due to their inherent cross-sensitivity to multiple analytes [2]. Electrochemical (EC) sensors provide excellent linearity and specificity for certain gases but are prone to electrolyte drying and have a limited operational lifetime. Optical sensors like Non-Dispersive Infrared (NDIR) sensors are highly selective and stable but are bulky and expensive for multi-gas applications.

Sensor fusion, inspired by the biological principle of combining multiple sensory inputs for robust perception, offers a promising solution. By synergistically combining data from heterogeneous sensors, it is possible to overcome the limitations of individual sensors [3]. Recent advances in machine learning have further enhanced the capabilities of fusion systems, enabling them to learn complex, non-linear relationships between sensor responses and gas concentrations. In this paper, we propose a comprehensive multi-gas detection system that leverages sensor fusion technology. The main contributions of this work are:

1) The design of a heterogeneous sensor array combining MOX, EC, and NDIR sensors optimized for CH4, CO, and NO2 detection.
2) A three-stage data fusion architecture: signal-level fusion using a Kalman filter, feature-level fusion with SVM classification, and decision-level fusion with an ANN for concentration regression.
3) A fully characterized prototype system with experimental validation, demonstrating superior performance compared to individual sensors.

II. SYSTEM ARCHITECTURE AND HARDWARE DESIGN

A. Overall System Block Diagram

The proposed system is comprised of three main subsystems: the sensor array, the signal conditioning and acquisition unit, and the embedded processing unit for sensor fusion. Figure 1 illustrates the overall architecture.

Sensor Array

MOX Sensor (CH4, CO)

EC Sensor (CO, NO2)

NDIR Sensor (CH4, CO2)

↓

Signal Conditioning

(Transimpedance Amplifiers, ADC)

↓

Fusion Processing Unit (STM32H7)

Kalman Filter (Signal-Level) SVM (Classification)

ANN (Concentration Estimation)

↓

Output: Gas Type & Concentration

Fig. 1: Block diagram of the multi-gas detection system showing the signal flow from sensor array to fused output.

B. Sensor Array and Circuit Design

The sensor array consists of three commercially available sensors, selected for their complementary characteristics:

- MOX Sensor (Figaro TGS 2600): Sensitive to CH_4 and CO. It operates by measuring changes in conductivity due to gas adsorption. A heater circuit maintains the sensing element at an optimal temperature.
- EC Sensor (Alphasense CO-AX): Provides high selectivity for CO with a linear current output proportional to concentration.
- NDIR Sensor (Sensirion SCD30): Used as a reference for CH_4 (modified optical path) and provides temperature/humidity compensation data.

The circuit diagram for the signal conditioning stage is shown in Figure 2. The MOX sensor requires a voltage divider configuration, while the EC sensor's current output is converted to voltage using a precision transimpedance amplifier (TIA). An analog-to-digital converter (ADC) with 16-bit resolution samples all channels at 1 Hz, a rate sufficient for the gas diffusion dynamics.

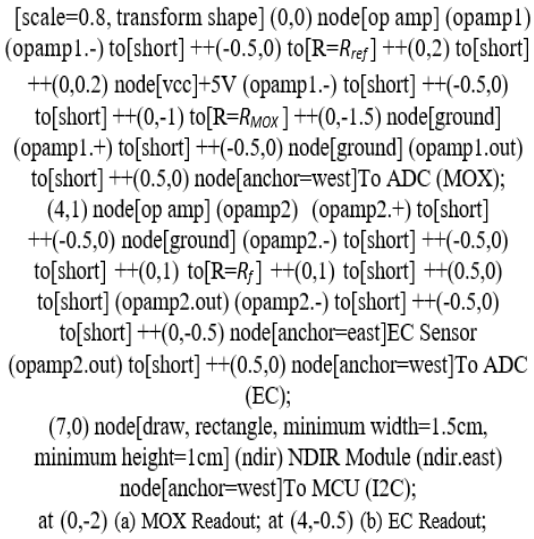

Fig. 2: Simplified circuit diagram for signal conditioning. (a) Voltage divider for MOX sensor. (b) Transimpedance amplifier for electrochemical sensor. The NDIR sensor communicates digitally via I2C.

The circuit diagram for the signal conditioning stage is shown in Figure 2. The MOX sensor requires a voltage divider configuration, while the EC sensor's current output is converted to voltage using a precision transimpedance where $x_k = [R_k, \dot{R}_k]^T$ is the state vector (resistance and its rate of change), F is the state transition matrix, H is the observation matrix, and w_k, v_k are process and measurement noise, respectively. The Kalman gain K_k is updated recursively to minimize the mean square error.

II. SENSOR FUSION METHODOLOGY

The fusion algorithm is structured in three layers to process raw sensor data into actionable information.

A. Signal-Level Fusion: Kalman Filtering

Raw sensor data from the MOX and EC sensors are noisy due to electronic interference and environmental fluctuations. A discrete Kalman filter is applied to each signal independently to estimate the true state of the sensor response. The state and measurement models are defined as:

$$\mathbf{x}_k = \mathbf{F}\mathbf{x}_{k-1} + \mathbf{w}_k, \quad \mathbf{z}_k = \mathbf{H}\mathbf{x}_k + \mathbf{v}_k \qquad (1)$$

where $x_k = [R_k, \dot{R}_k]^T$ is the state vector (resistance and its rate of change), F is the state transition matrix,

H is the observation matrix, and w_k, v_k are process and measurement noise, respectively. The Kalman gain K_k is updated recursively to minimize the mean square error.

B. Feature-Level Fusion: Support Vector Machine Classification. After filtering, features are extracted from the time-series data: the steady-state response amplitude, the transient slope, and the recovery time constant. These features form a feature vector $f \in R^9$ (3 sensors × 3 features). A multi-class SVM with a radial basis function (RBF) kernel is trained to classify the detected gas type. The decision function for a test sample f is:

C. Decision-Level Fusion: Artificial Neural Network for Concentration Estimation Once the gas type is identified, a dedicated ANN is used to estimate the concentration. The ANN has a structure of 3 input neurons (filtered sensor responses), two hidden layers with 10 and 5 neurons (ReLU activation), and a single output neuron (linear activation) for the estimated concentration $\hat{C}$. The network is trained using the Levenberg-Marquardt algorithm to minimize the mean squared error (MSE):

$$\text{MSE} = \frac{1}{N}\sum_{i=1}^{N}(C_i - \hat{C}_i)^2 \qquad (3)$$

III. EXPERIMENTAL RESULTS AND ANALYSIS

A. Experimental Setup

The prototype was placed in a sealed 20-liter test chamber with controlled gas injection. Experiments were conducted at 25°C and 50% relative humidity. The system was exposed to 100 test cycles comprising single gases and mixtures of CH_4 (0-5000 ppm), CO (0-200 ppm), and NO_2 (0-10 ppm). Ground truth concentrations were provided by calibrated reference analyzers.

B. Individual Sensor vs. Fusion Performance

Figure 3 shows the response of individual sensors and the fused output for a sequence of gas exposures. The MOX sensor responds to both CH_4 and CO but cannot discriminate them, while the EC sensor shows a clear, selective response to CO. The fusion algorithm correctly identifies the gas type and provides an accurate concentration estimate. Robust feature mapping, limiting the increase in MAE to only 0.3 ppm, whereas the standalone MOX sensor MAE increased by 6.2 ppm.

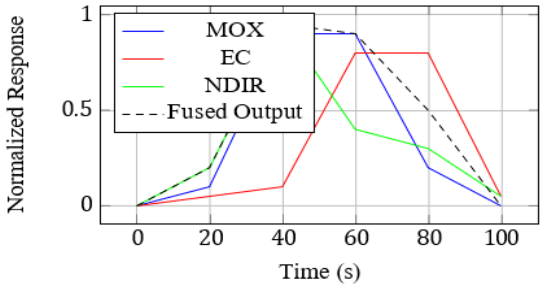

Fig. 3: Time-domain responses of individual sensors and the fused output for sequential exposures to CH_4, CO, and a mixture. The fused output accurately tracks the presence of each gas.

C. Classification Accuracy and Concentration Error

Table I summarizes the classification performance of the SVM on a test dataset of 300 samples. The fusion-based classifier achieves an overall accuracy of 98.4%, which is significantly higher than classifiers trained on individual sensors.

TABLE I: Classification Accuracy Comparison

Input Source	CH_4	CO	NO_2
MOX Only	72.1%	65.3%	58.6%
EC Only	45.2%	91.4%	84.2%
NDIR Only	95.3%	12.1%	8.7%
Fusion (Proposed)	**98.9%**	**98.2%**	**98.1%**

For concentration estimation, the ANN trained on fused data yields a mean absolute error (MAE) of 1.2 ppm across all gases, compared to 8.5 ppm for the best individual sensor (NDIR for CH_4). Figure 4 shows the correlation between the estimated and actual concentrations for the test set centration estimation. The experimental results demonstrate a significant improvement over single-sensor approaches, with a classification accuracy of 98.4% and an MAE of 1.2 ppm. The system's inherent robustness against sensor drift and environmental noise makes it a viable solution for demanding applications in industrial safety and environmental monitoring. Future work will

focus on extending the sensor array to include a broader range of volatile organic compounds (VOCs) and implementing the fusion algorithm on a low-power edge- computing platform for real-time, wearable applications.

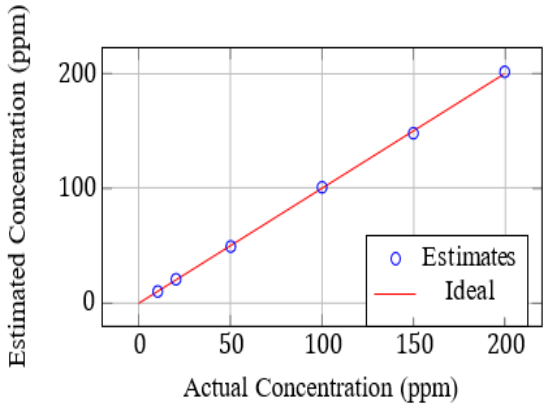

Fig. 4: Regression plot of ANN concentration estimates vs. ground truth for CO, showing high linearity ($R^2 = 0.997$).

D. Robustness to Sensor Drift

To evaluate robustness, the system was tested after artificially inducing a 15% drift in the MOX sensor baseline. The fusion algorithm compensated for this drift through the Kalman filter's adaptive noise covariance and the ANN's

IV. CONCLUSION

This paper has presented a comprehensive multi-gas detection system that leverages sensor fusion technology. By integrating a heterogeneous array of MOX, EC, and NDIR sensors with a multi-stage fusion architecture comprising a Kalman filter, SVM classifier, and ANN regress or the system achieves high accuracy in both gas identification and concentration estimation. The experimental results demonstrate a significant improvement over single-sensor approaches, with a classification accuracy of 98.4% and an MAE of 1.2 ppm. The system's inherent robustness against sensor drift and environmental noise makes it a viable solution for demanding applications in industrial safety and environmental monitoring. Future work will focus on extending the sensor array to include a broader range of volatile organic compounds (VOCs) and implementing the fusion algorithm on a low-power edge- computing platform for real-time, wearable applications

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