Rapid Recognition of Olfactory Scenes with a Portable MOx Sensor System using Hotplate Modulation

Damien Drix*†, Nik Dennler*†‡ and Michael Schmuker†§
† *Biocomputation Research Group*, *University of Hertfordshire*, Hatfield, United Kingdom
‡ *International Centre for Neuromorphic Systems*, *Western Sydney University*, Sydney, Australia
* Equal contribution
§ Corresponding author. Email: m.schmuker@herts.ac.uk

***Abstract*—A café, the metro, a supermarket, a book store — many locations of everyday life have a specific smell. Recognising such olfactory scenes could inform personal activity tracking, environmental monitoring, and assist robotic navigation. Yet it is unclear if current Metal-oxide (MOx) sensor technology is sensitive and specific enough to achieve this. Factors like sensor drift, and sensitivity to ambient humidity and temperature further complicate the recognition of olfactory scenes. Hotplate temperature modulation has been suggested as a method to counter these drawbacks. We present an electronic nose based on MEMS-MOx sensors that support rapid hotplate temperature modulation with a 150 ms period. We recorded different natural olfactory scenes in an urban context. A linear SVM was able to recognise four olfactory scenes in single hotplate cycles with near-perfect performance when trained and tested on the same day, and 73% accuracy when tested in the same locations on the next day. Gas sensor responses yielded higher recognition accuracy than humidity, temperature, and pressure that were also partly-location specific. Our results indicate that hotplate modulation enables recognition of natural odor scenes across extended timespans. These findings encourage the use of MOx-sensors as rapid sensing devices in natural, uncontrolled environments.**

***Index Terms*—Natural odor scene recognition, Metal oxide sensors, Hotplate modulation**

I. INTRODUCTION

The use of electronic noses (eNoses) has become popular in many areas, such as industrial and environmental monitoring [1], hazard control [2], mobile olfactory robotics [3], and medical screening [4]. Despite shortcomings like drift and cross-sensitivity to humidity, MOx sensors are an attractive choice for electronic noses due to their low cost and availability. The current generation of sensors are made using MEMS techniques which enable faster modification of the sensing site temperature, and these fast modulation cycles have been shown to decrease the integration time and improve the specificity of the responses to different analytes [5].

The recognition of olfactory scenes is an interesting but challenging problem, as it requires a portable eNose [6] that can operate in uncontrolled natural environments susceptible to changes in temperature, humidity and pressure.

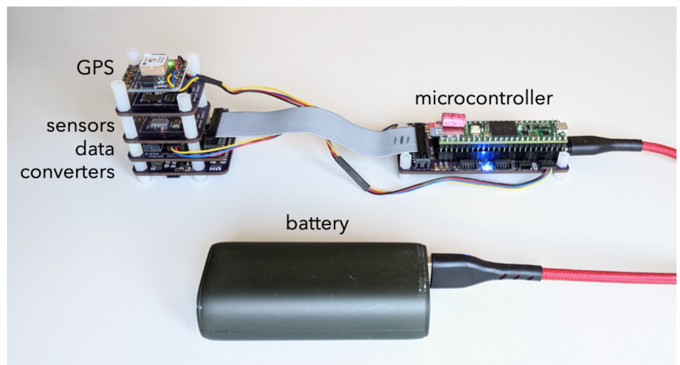

Fig. 1. Overview of the electronic nose system, showing the sensor board, microcontroller board and power source.

II. ENOSE DESIGN

We designed an electronic nose with three goals in mind: (1) to investigate heater modulation techniques, (2) to take advantage of MEMS gas sensors and their faster response times, and (3) to enable field recordings untethered to a computer. Our design uses off-the-shelf components and consists of two main parts: a microcontroller board based on a Teensy 4.1 microcontroller (PJRC.com) for data processing and storage, and a sensor board hosting the sensors, associated analog circuitry, and data converters, in a portable unit (fig. 1).

We use four metal-oxide sensors grouped in three MEMS packages: MiCS 4514 and MiCS 5914 (SGX Sensortech) and CCS801 (AMS/ScioScience). These can sense various kinds of reducing and oxidising gases including various volatile odor compounds (VOCs), hydrocarbons, carbon monoxide, hydrogen, nitrogen oxides and ammonia.

Heater modulation requires a way to measure the hot plate temperature, and a way to regulate the power delivered to the resistive heating element. In metal-oxide gas sensors with resistive hotplates, the heater resistance increases quasi-linearly with temperature. Absolute hotplate temperature can be estimated by continuously measuring the heater resistance, combined with calibration information obtained from the manufacturer's datasheet. We use a DAC (DAC7554, Texas

Instruments) and an amplifier (TS924, STMicroelectronics) to set the voltage, and a sense resistor of known fixed value to measure the resulting current (fig. 2). This enables control of the heater resistance, temperature, and power.

The gas sensor response fluctuates rapidly with the hot plate temperature, independently from the speed at which chemical reactions occur on the sensor surface (fig. 3b). We therefore sample the hotplates and sensors synchronously, using two simultaneously-sampling, 8-channel ADCs (ADS131M08, Texas Instruments). These form a closed control loop with the DAC, running at 1 kHz. The high sampling rate is is required to support accurate control of the heating elements, which have thermal time constants on the order of 20 ms.

A GPS module provided position and time. One environmental sensor measured the temperature and humidity in close thermal proximity to the sensors (MS8607 from TE Connectivity, also providing barometric pressure). Another sensor measured the temperature and humidity of the surrounding air, uninfluenced by the heaters (SHT31 from Sensirion). The microcontroller recorded the data on-the-fly to an SD card at a data rate of 150 kB/s, enabling multiple-hour recordings.

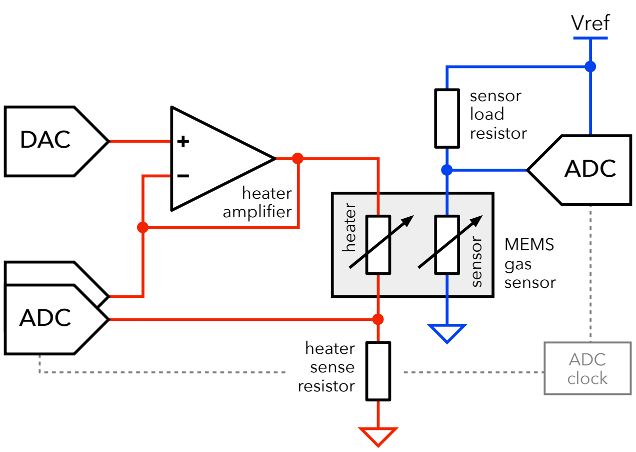

Fig. 2. Simplified schematic of the sensor board showing one out of four sensor channels. Each channel contains its own heater circuit (in red) and gas sensor circuit (in blue). The heater amplifier tracks the DAC voltage (gain=1) and supplies the required heater current (up to 35 mA).

III. Data Collection

We acquired a dataset of natural olfactory scenes recorded in different urban indoor locations: 'Café', 'Metro', 'Bookstore' and 'Supermarket'. Each location was visited once per day, on two consecutive days. We recorded the four gas channels, ambient temperature, relative humidity, and pressure. Heater power was modulated with a period of 150 ms as described in fig. 3.

The data was divided into training and testing sets with a four-fold cross-validation procedure. For each day and location, we selected a contiguous block containing 25% of the data and randomly picked 400 heater cycles from this block for testing. We then drew 1200 training cycles from the remaining 75% of the data. The whole procedure was repeated four times with non-overlapping test blocks, to allow the models to be validated on the entire dataset. This yielded a total of 12800 cycles divided in four sets: training (day 1), testing (day 1), training (day 2) and testing (day 2).

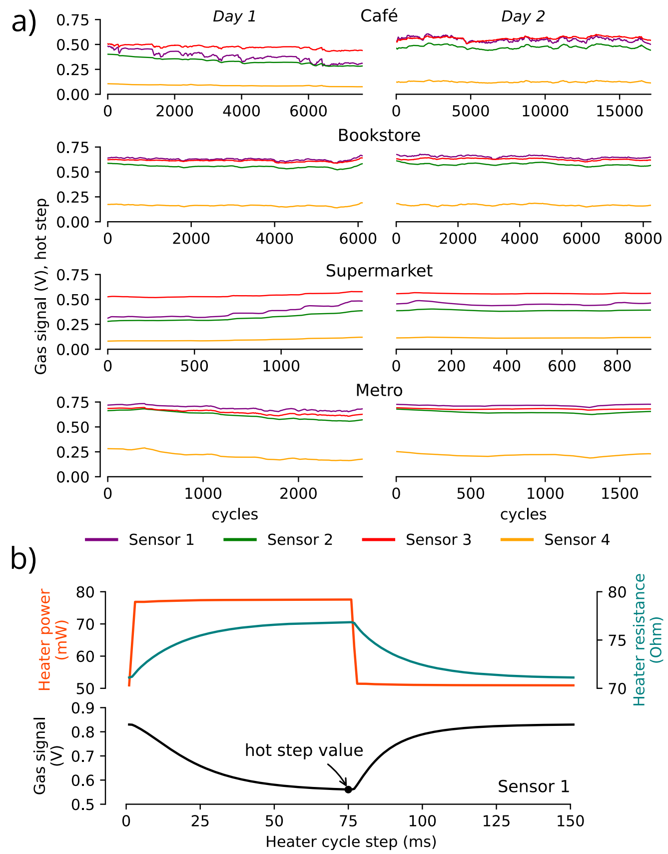

Fig. 3. Overview of the gas sensor data. a) Gas sensor response at the hottest part of each heater cycle, across four locations visited on two different days. b) Schematic of the heater modulation cycle. Each cycle steps between two fixed power levels (different for each channel) with a 150ms period. Hot plate temperature is inferred from heater resistance. Volatiles and environmental factors affects the shape of the temperature-induced response of the gas sensors.

IV. Inference of Olfactory Scenes from Baseline-Normalised Sensor Cycles

We then investigated whether one can recover the label of the olfactory scene from the time course of a single 150 ms heater cycle, either from the gas sensor conductance or from the environmental sensors.

First, the gas signal was normalised to the same minimum and maximum values over each heater cycle (fig. 4a). This mitigates the baseline drift often seen in gas sensor datasets [7], which is problematic for classification tasks [8]. While this normalisation step yields curves that, at first sight, look very similar across locations, they differ substantially and reproducibly if one compares them closely (see insets in fig. 4a). Observing the 2D projections in the space of principal components (fig. 4b), separable and class-aligning clusters emerge not only for for single day recordings, but also for the entire data spanning two days.

If one considers the environmental sensor responses (fig. 4c), it is evident that at each location there is a drift in temperature and humidity, causing a strong overlap of the responses across the classes, making a separation challenging. While pressure is more stable for each class at a given day, there appears to be an offset when comparing different days.

Those qualitative observations are confirmed by evaluating a linear classifier trained on a subset of the data. For the different sensors (temperature, humidity, pressure, gas), all possible combinations are formed and the respective day-1 training set is used to train a soft-margin, linear-kernel Support-Vector-Machine (SVM) [9]. Each model is then validated via the classification accuracy achieved on the day-1 testing set and on the day-2 testing set (fig. 4d). When training and testing on data from the same day (day 1), the model trained on the gas sensor responses achieves the highest accuracy scores by a large margin (97.2% validation accuracy vs. 49.6%, 31.2% and 85.6% for temperature, humidity and pressure respectively). When training on day 1, and testing on day 2, again the gas sensor results surpass the ones achieved by having the environmental sensors only (72.8% validation accuracy vs. 52.3%, 31.3% and 25.0%). In both cases, there seems to be no obvious advantage in combining the gas sensors with any of the environmental sensors.

V. Conclusion

In this work, we presented a novel design for a portable eNose, which takes advantage of the properties of state-of-the-art MEMS gas sensors, allowing high-frequency heater control and sensor readout. We demonstrate that the phase-locked sensor response relative to heater cycles constitutes a promising feature for classifying natural olfactory scenes from sub-second samples. Further, we showed that the information present in the gas sensor signal does not appear to be fully explained by cross-sensitivities to the ambient air temperature, humidity and pressure: each location's unique olfactory signature seems to play a role as well. Future work should focus on evaluating the reproducibility of olfactory scene recognition across a wider range of conditions, and over longer intervals of time.

Acknowledgment

We thank A. v. Schaik and S. Rastogi for fruitful discussions at multiple occasions, which led to valuable insights. D.D. and M.S. were funded from EU H2020 Grants Human Brain Project SGA2 and SGA3 (#785907 and #945539). M.S. received additional funding from the joint MRC/NSF grant "NeuroNex: From Odor to Action" (#MR/T046759/1 and #2014217).

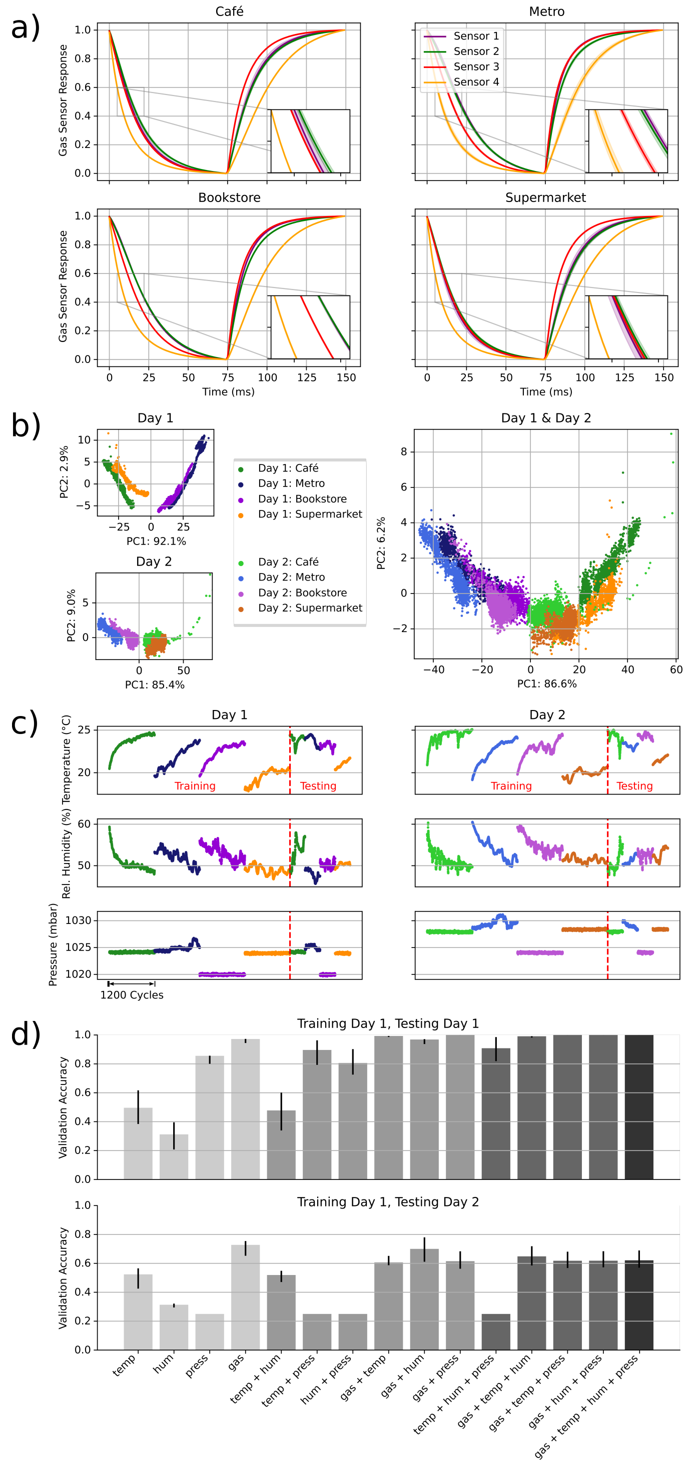

Fig. 4. Analysis results. a) Normalised gas sensor cycles in four locations. b) PCA projection of sensor responses. Left: separate days, right: both days in joint PC space. c) Environmental variables of one cross-validation train-test split overlap for the different classes (one value per cycle). d) Validation accuracies for an SVM classifier, for different sensor modalities and their combinations.

References

[1] R.E Baby, M Cabezas, and E.N Walsöe de Reca. Electronic nose: a useful tool for monitoring environmental contamination. *Sensors and Actuators B: Chemical*, 69(3):214–218, 2000. Proceedings of the International Symposium on Electronic Noses.

[2] Ana Solórzano, Jens Eichmann, Luis Fernández, Bernd Ziems, Juan Manuel Jiménez-Soto, Santiago Marco, and Jordi Fonollosa. Early fire detection based on gas sensor arrays: Multivariate calibration and

validation. *Sensors and Actuators B: Chemical*, 352:130961, 2022.
[3] Achim J. Lilienthal, Amy Loutfi, and Tom Duckett. Airborne chemical sensing with mobile robots. *Sensors*, 6(11):1616–1678, 2006.
[4] Frédéric Loizeau, Hans Peter Lang, Terunobu Akiyama, Sebastian Gautsch, Peter Vettiger, Andreas Tonin, Genki Yoshikawa, Christoph Gerber, and Nico de Rooij. Piezoresistive membrane-type surface stress sensor arranged in arrays for cancer diagnosis through breath analysis. In *2013 IEEE 26th International Conference on Micro Electro Mechanical Systems (MEMS)*, pages 621–624. IEEE, 2013.
[5] Alexander Vergara, Kurt D. Benkstein, Christopher B. Montgomery, and Steve Semancik. Demonstration of fast and accurate discrimination and quantification of chemically similar species utilizing a single cross-selective chemiresistor. *Analytical Chemistry*, 86(14):6753–6757, 2014.
[6] Lu Cheng, Meng Hao, Achim Lilienthal, and Pei-Feng Qi. Development of compact electronic noses: A review. *Measurement Science and Technology*, 32, 03 2021.
[7] Alexander Vergara, Shankar Vembu, Tuba Ayhan, Margaret A. Ryan, Margie L. Homer, and Ramón Huerta. Chemical gas sensor drift compensation using classifier ensembles. *Sensors and Actuators B: Chemical*, 166-167:320–329, 2012.
[8] Nik Dennler, Shavika Rastogi, Jordi Fonollosa, André van Schaik, and Michael Schmuker. Drift in a popular metal oxide sensor dataset reveals limitations for gas classification benchmarks. *Sensors and Actuators B: Chemical*, 361:131668, jun 2022.
[9] Corinna Cortes and Vladimir Vapnik. Support-vector networks. *Machine learning*, 20(3):273–297, 1995.