Rapid Inference of Geographical Location with an Event-based Electronic Nose

Nik Dennler* †
Biocomputation Research Group,
University of Hertfordshire
Hatfield, UK

Damien Drix*
Biocomputation Research Group,
University of Hertfordshire
Hatfield, UK

Shavika Rastogi‡
International Centre for
Neuromorphic Systems, Western
Sydney University
Sydney, AU

André van Schaik‡
International Centre for
Neuromorphic Systems, Western
Sydney University
Sydney, AU

Michael Schmuker§
Biocomputation Research Group,
University of Hertfordshire
Hatfield, UK

KEYWORDS

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INTRODUCTION

Sensory information is crucial for the successful interaction of an agent with its outside world. How sensory stimuli are optimally encoded remains an open research question. Neuro-inspired coding strategies have been successfully applied to many tasks dealing with vision, auditory perception, touch and vibration sensing [3, 6, 11, 17]. For the sense of olfaction, there still exists a large performance gap between artificial and biological systems [5]. This is particularly evident if one considers the fast-changing odour distribution caused by air turbulences. The fluctuation frequencies in an odour plume are governed by a power law [13] and can carry essential information about the odour source [15].

While mammals can discriminate temporal correlations of rapidly fluctuating odours at frequencies of up to 40 Hz [1], metal-oxide (MOx) gas sensor based olfactory systems usually have response times that are several orders of magnitude slower [14]. Methods for improving the response time have been investigated [8, 9].

*Both authors contributed equally to this research.
†Also with International Centre for Neuromorphic Systems, Western Sydney University, Sydney, AU
‡Also with Biocomputation Research Group, University of Hertfordshire, Hatfield, UK
§Corresponding author. Email: m.schmuker@herts.ac.uk

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Latest-generation MOx gas sensors actively modify the sensing site using temperature modulation cycles, which decreases the integration time and increases the class discriminability [20]. Yet it remains unclear how much information is present in one cycle's sensor response and how to efficiently sample it. Here, contrary to a top-down approach from biological olfaction to neuromorphics [10], we propose a data-driven asynchronous event-sampling strategy for state-of-the-art gas sensors, and investigate the effectiveness of different event encoding schemes for solving an inference problem.

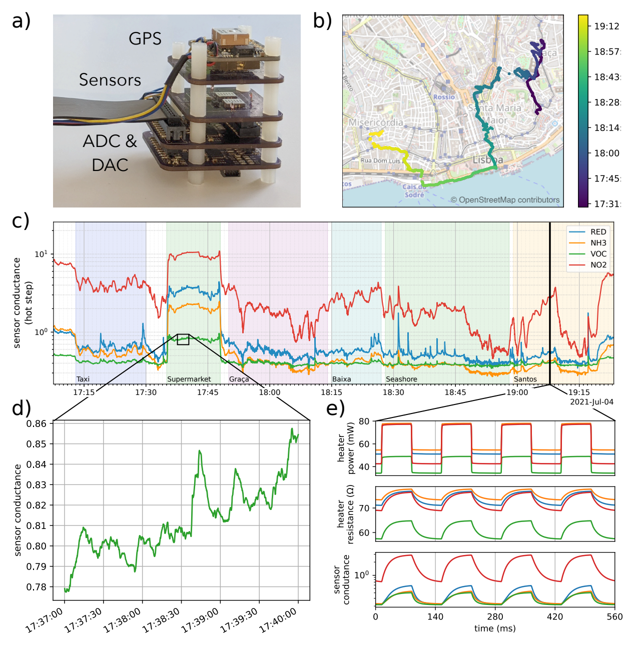

Figure 1: a) Portable multichannel e-nose. b) GPS track of the recording. c) MOx sensor data, showing the sensor conductances at the end of the high-temperature step. d) Zooming in reveals structure on a timescale of seconds to minutes. e) Cyclic heater power modulation (top) drives sub-second oscillations in heater temperature (middle, shown as heater resistance) and sensor conductance (bottom).

METHODS

We constructed a portable electronic nose equipped with four different MOx gas sensors (*SGX Sensortech* `MiCS5914` & `MiCS4514` dual sensor, *ScioSense* `CCS801`) and recorded the natural olfactory scenes encountered during a walk through the city of Lisbon, Portugal, dividing the dataset into six geographical locations (hereafter labelled 'Taxi', 'Supermarket', 'Graça', 'Baixa', 'Seashore', and 'Santos'). We sampled the conductance of the gas sensing elements at 1 kHz while modulating the heater power with a period of 140 ms, each heater cycle consisting of a high-power step followed by a low-power step. This causes the sensor conductance to oscillate in a way that depends on the heater temperature, the environmental conditions, and the gases present in the sensor cavity (fig. 1).

We then investigated whether we could recover the geographical label from the time course of the sensor conductance during a single 140 ms heater cycle. Crucially, each cycle was normalised to the same minimum and maximum values (fig. 2a), thus getting rid of the baseline drift that often compromises gas sensor datasets [7, 21], leaving only the intra-cycle variations to distinguish between different locations. For each normalised cycle, we construct a signal that highlights these intra-cycle variations by subtracting a sensor-specific model curve, which, in our case, is the ensemble average of the normalised cycles across a subset of the data (fig. 2b). We apply an algorithm based on *send-on-delta sampling* [12, 19] to generate up- and down-events when the signal changes, exploring a range of spike (event) thresholds. These events are then used to compute four different features: the channel-wise event rate (rate code), the channel-wise time-to-first-spike (latency code, [18]), the channel order of first spikes (rank code, [16]), and a signal reconstruction using the reverse *send-on-delta sampling* algorithm (fig. 2c). The representations resulting from each of the four encoding strategies are divided into training and test sets with a ratio of 75% to 25%, by sampling a total of 2000 cycles per class from time-separated bulks as described in [2]. For each spiking threshold and each encoding strategy, a linear-kernel Support-Vector-Machine (SVM) [4] was fitted to the training set and validated on the test set.

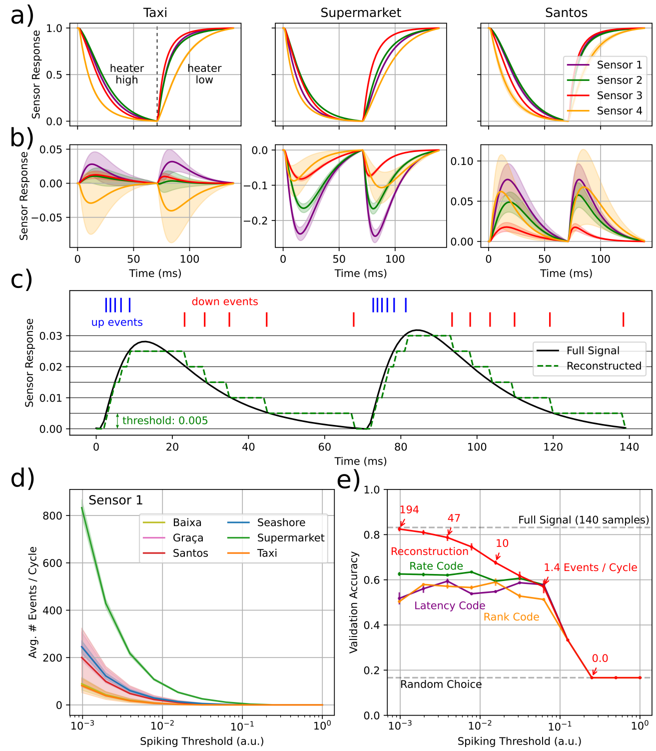

Figure 2: a) The normalised sensor conductance oscillates between fixed minima and maxima. b) After subtracting the mean, intra-cycle variations reveal distinct patterns across geographical locations. Solid lines and shading correspond to mean and one standard deviation. c) Example event generation and reconstruction (Sensor 1, location: taxi) d) The average number of events per cycle decreases with increasing spiking threshold, but varies across locations (data for Sensor 1). e) Classification accuracy for different encoding schemes vs. spiking threshold (mean and standard deviation for twelve train/test splits).

RESULTS AND DISCUSSION

All four encoding strategies perform better than chance levels (fig. 2e). The signal reconstructed from events performs as well as the original intra-cycle signal when the event count is high (82.5±1.0% vs. 84.2±1.2%). Accuracy then decreases as the event threshold increases (fewer events, see fig. 2d). While latency code, rank code and rate code representations provide a high signal compression (one value per up- and down channel for each sensor), they are outperformed by the reconstructed curve, until the number of events was reduced to 1% of the original signal's sample count.

Our findings indicate that various olfactory scenes can be distinguished based on the differential time course of sensor conductance during individual sub-second heater cycles, despite a normalisation procedure that removes information about absolute sensor conductance. Furthermore, the full temporal pattern of events within each cycle seems to matter for scene recognition. This hints at a phasic component in the sensor response to a temperature step that contributes to the classification accuracy. Whether this phasic component stems from the temperature-specific reactivity of various gases or from other influences not excluded by our normalisation procedure remains to be investigated.

CONCLUSION

We propose an event-based sampling scheme to represent cyclic heater-modulated electronic nose data. Asynchronous sampling captured the signal's temporal dynamics better than rate-, rank- or latency-codes, while recognition accuracy degraded gracefully for reduced event counts. Our work paves the way for event-based recognition of natural odor scenes in uncontrolled environments, breaking new ground in neuromorphic gas sensing.

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