Resolving fast transients with Metal-Oxide gas sensors

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Abstract

Electronic olfaction can help detect and localise harmful gases and pollutants, but the turbulence of natural environment presents a particular challenge: odor encounters are intermittent, and an effective electronic nose must therefore be able to resolve short odor pulses. The slow responses of the widely-used Metal-Oxide (MOX) gas sensors complicate the task. Here we combine high-resolution data acquisition with a processing method based on Kalman filtering and absolute-deadband sampling to extract fast transients. We find that our system can resolve the precise time of odor onset events, allowing direction estimation with a pair of MOX sensors in stereo-osmic configuration.

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Electronic olfaction has potential in many areas such as industrial and environmental monitoring and safety, where it can help detect and localise harmful gases or pollutants.

But in natural environments, odors are dispersed by turbulent plumes and encounters are intermittent\(^1\). The temporal statistics of short odor pulses (hereafter called *bouts*) contain information about source location\(^2\). An effective electronic nose needs to resolve these bouts.
Metal-Oxide (MOX) gas sensors are widely used, but have impulse response durations in the order of tens to hundreds seconds, and are therefore often thought to be unable to resolve short odor pulses, which would limit their utility in turbulent environments.

However, a large part of the impulse response is due to a slow sensor recovery phase, in the order of 100s, in which the sensor conductance slowly returns to baseline while the initial reaction of the volatile with the sensor electrode is reversed. The onset of the response is near-instantaneous and can be detected after fractions of a second. Therefore, fast transients could be detectable with appropriate hardware and signal processing that separate the initial binding from the recovery phase.

Here we built new hardware to acquire data from multiple MOX sensors with increased bit depth and sampling rate. We developed a signal processing method based on a Kalman filter and absolute deadband sampling to extract bout detection events and encode their onset time. We demonstrate the device’s improved temporal resolution in a stereo-enose setup that detects the source direction of short odorant bouts.

Our gas sensor boards consist of four metal-oxide (MOX) sensors and a high-resolution analog-to-digital converter (ADC). We use four sensors manufactured by Figaro Inc. (Osaka, Japan): TGS2600, TGS2602, TGS2610 and TGS2620, to cover a wide range of target gases. The ADC (ADS122C04, Texas Instruments) offers 24 bits of resolution and can sample all four sensor channels at a frequency of up to 200 Hz. As MOX sensors are affected by ambient temperature and humidity, the boards can also host an optional 16-bit digital temperature and humidity sensor (SHT31-DIS, Sensirion).

An I2C bus operating at 800 KHz connects the boards to a microcontroller (Teensy 4.0, PJRC.COM) that reads out the data and transmits it to the host computer via USB (fig. 1). The system is set up so that the microcontroller can handle multiple sensors in parallel, for instance left and right electronic noses in a stereo configuration.

The gas sensors are connected to the ADC in the voltage divider configuration that is standard for this type of sensor (fig. 1). The sensing element (RS) is in series with a
Figure 1: **Simplified schematic of the sensor boards.** The ADC on each sensor board measures the voltage across the MOX sensing elements RS. A separate 5V supply powers the heating elements RH. The sensor board communicates via I2C with a Cortex-M7 microcontroller that transmits the data to the host computer.

68 kΩ load resistor (RL) and the ADC performs a ratiometric measurement of the sensor voltage relative to the supply voltage, which cancels out common-mode noise. For a good compromise of dynamic range and resolution, we choose the load resistance $RL$ within an order of magnitude of the baseline resistance of the sensors in air, and continuously adjust the ADC’s input gain to maintain sensitivity over a large concentration range (fig. 2).

The ADC measures a ratio $x = \frac{V_S}{V_S + V_L}$, where $V_S$ and $V_L$ are the voltages across RS and RL, respectively. From this we compute the relative conductance $g_{rel}$ of each sensor relative to its load resistor:

$$g_{rel} = \frac{g_S}{g_L} = \frac{V_L}{V_S} = \frac{1}{x} - 1$$

Then, we divide by the baseline values at the start of each recording to get the normalised sensor conductance $g$ at time $t$:

$$g(t) = \frac{g_{rel}(t)}{g_{rel}(0)}$$

The purpose of the normalisation is to use the same parameters for processing multiple sensors with different characteristics. It is not fundamentally required, since none of the algorithms assume a specific or constant baseline value for $g$.

We deliver puffs of isopropyl alcohol (IPA) to the sensors by means of a soft plastic bottle.
Figure 2: **Automatic input gain selection maintains sensitivity over a large input range.** ADC measurement for a varying sensor resistance $R_S$ at different gain settings. $R_S$ follows an approximate power law with respect to gas concentration; thus it makes sense to use a logarithmic scale, where the slope of the measurement function indicates the sensitivity to a relative change (e.g. $\pm 1\%$). The input gain changes from 1x to 4x at predefined thresholds (thin arrows) to avoid the regions of lower slope.

Figure 3: **An automated setup delivers puffs of odorant towards stereo sensor boards.** A: Side view of the system in its left-to-right configuration. B, inset: top view of a sensor board showing the position of the four sensors in relation to the stimulus axis.
(NeilMed Inc, USA) squeezed by a servomotor to force some of the vapours out of the nozzle (fig. 3). This creates a sharp puff that we could observe up to 50 cm from the nozzle in a quiet atmosphere.

We record simultaneously from two identical boards placed along the direction of travel of the puff. This yields four pairs of stereo channels (S0 to S3), one for each MOX sensor type. We aim the stimuli slightly downwards onto a flat surface and position the top of the MOX sensors flush with that surface to reduce turbulence caused by the sensors themselves, which might otherwise disrupt the narrow odor plume before it reaches sensors on the far side. We record one dataset with the stimulus traveling in the left-to-right direction, then move the bottle to the other side and record another dataset for the right-to-left direction.

MOX sensors respond to puff of odorants with a fast rising phase, followed by a slower decay back to baseline (fig. 4 A). This slow decay can mask fast transients, for instance when two bouts occur close together in time (see e.g. fig. 5 A). The goal of post-processing is to recover fast transients from the onset dynamics, thus providing the ability to resolve short odor pulses. Various solutions have been explored in previous work, such as taking the second derivative or deconvolution based on an estimate of the sensor’s impulse response function, blind deconvolution, and band-pass filters.

Here we use a constant-acceleration Kalman filter to compute a denoised estimate of the second derivative of the signal. The second derivative peaks at the onset of each puff (fig. 4 A). However it also has a second, smaller positive peak when the relaxation slows down, since that registers as a positive acceleration (fig. 4 B). As this could cause spurious bout detections we modify the filter to suppress the second peak. We do this by incorporating an exponential decay term into the system equations for the first derivative v, thus removing it.
Figure 4: Kalman filtering recovers the onset of odorant bouts. **A**: conductance $g$ and its second derivative $a$ estimated by the Kalman filter. **B**: Zooming in shows the effect of the filter parameter $\tau$ on the late-phase response. The arrowhead marks the stimulus time.
from the residual second derivative $a$:

\[
g(t + dt) = g(t) + v(t) dt + \left( a(t) - \frac{v(t)}{\tau} \right) \frac{dt^2}{2}
\]

\[
v(t + dt) = v(t) + \left( a(t) - \frac{v(t)}{\tau} \right) dt
\]

\[
a(t + dt) = a(t)
\]

The parameter $\tau$ sets the time constant of the exponential decay. We estimate it empirically for each sensor type, selecting the highest value which still suppresses the second peak.

For further processing we transform the continuous variable $a$ into an event-based representation. We employ a modulation technique that encodes changes in the variable’s value as a stream of binary events. If the variable’s value at a time $t$ is $f(t)$ and the time of the last event is $t_{\text{prev}}$, then a new event is emitted whenever the value has changed by more than a certain threshold $\theta$:

\[
f(t) - f(t_{\text{prev}}) > \theta
\]

With a constant threshold $\theta = 0.02$, the method is related to absolute deadband sampling; the event-based DVS camera uses a similar technique, but with logarithmically-spaced thresholds.

The algorithm yields a stream of onset events with a frequency proportional not to the signal $f$, but to its derivative $\dot{f}$. Since we want to encode $a$, not $\dot{a}$, we must first integrate it as a variable $o = \int a \, dt$, which we call **bout velocity** as it is analogous to the first filter derivative $v$ with the second peak removed. We obtain a burst of events at the onset of each bout (fig. 5); we find that the method is able to separate two stimuli separated by 5 seconds, a much shorter delay than the recovery phase of the sensor conductance.

We apply this event-based encoding to the data obtained from our recording setup in stereo-osmic configuration (fig. 3). As the stimulus travels over the sensors, the left and right sensor boards will detect its onset at slightly different times, with the delay between
Figure 5: Events generated from the bout velocity variable isolate the onset of each bout. Responses of two sensor pairs during the same trial with two puffs of odorant (arrowheads) at a 5-second interval in the right-to-left direction. 

A, B: conductance $g$ and bout velocity $o$ estimated by the Kalman filter for the TGS2602 sensors (left & right), together with the resulting events (vertical lines), and their time-histograms on top. 

C, D: same as A & B, but with the TGS2620 sensors, which have a faster response time.
Figure 6: **Relative delays between left and right channels encode the direction of travel.** Shown here are the delays between the first event on the left channel and the first event on the right channel over 40 trial runs, colour-coded by stimulus direction (20 trials with a left-to-right puff and 20 with a right-to-left puff). Three outliers with a delay greater than 2 seconds are not shown on this graph.

left and right boards depending on the speed and direction of the puff. We extract the time of the first event on each sensor channel, and then compute the time differences between the left and right sensors (fig. 6). We find that the sign of that time difference encodes the direction of the stimulus unambiguously, despite some variance due to turbulent flow. A slight systematic offset is also apparent between between channels. We have observed a similar effect when the axis of the puff deviates from the center line; thus the offset may be due to lateral flow, although mismatched sensor characteristics may also play a role.

We employed signal processing and event-based encoding to resolve fast transients in the 1-second range using off-the-shelf metal-oxide sensors. Increased temporal resolution renders metal-oxide sensors more useful in extracting data from turbulent plumes, in particular when the temporal structure of gas concentration fluctuations is of concern, rather than absolute concentration values. Here we show that the timing of bout onset events is enough to estimate the direction of a puff of odorant. In a similar way, the frequency of these bout events was already known to contain information about the the distance to the source.
Future research should aim to confirm how well our approach translates to more challenging environmental conditions, for instance with more chaotic plumes and lower odorant concentration. The approach should be tested to assess to which extent event timing is sufficient to navigate towards an odor source.

The proposed method is inherently robust to baseline drift, a common issue with MOX sensors where their conductance at a certain odorant concentration will vary over the lifetime of the sensor. It also lessens the impact of the sensors’ cross-sensitivity to slow changes in ambient temperature and humidity.

Currently, wind-vane or ultrasound anemometers are often used to estimate odor source direction, as odorant plumes are carried along airflow. The proposed method may provide a low-cost alternative in space-constrained scenarios, like odor-guided robots.

Our work demonstrates how MOX sensors can resolve fast odor transients in turbulent environments. It highlights their potential for odor-guided navigation in embedded systems, for instance in weight-constrained aerial vehicles[8].

While the present work focused on temporal resolution, future research should assess whether particular odorants and mixtures of odorants can be reliably identified using the event-based approach. This would constitute a purely event-based system for the simultaneous identification and localisation of gas sources.

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