Odour Localization in Neuromorphic Systems

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***Abstract*—Odour source localization is crucial in life-saving scenarios like pinpointing gas leaks, detecting explosives, searching for earthquake survivors, or locating fires at their origin. The turbulent character of natural environments makes this task very challenging. The absolute concentration of odour plumes carries little meaning and these plumes are only encountered in an intermittent, transient fashion. However, navigation algorithms that are driven by odour encounter events, can successfully find odour sources by extracting spatiotemporal information. The event driven nature of odour plumes motivates a fully event-driven sensing and processing pipeline for robot navigation. Hence, we developed a spiking neural network, implemented on neuromorphic hardware, that can successfully decode odour-puff direction from a pair of enose-systems. This is to our knowledge the first fully event driven neuromorphic system for odour localization.**

I. Introduction

Odour source localization is crucial in life-saving scenarios like pinpointing gas leaks, detecting explosives, searching for earthquake survivors, or locating fires at their origin. However, finding an odour source in a natural environment is challenging due to the fact that all natural environments are turbulent. Therefore, odours do not form smooth concentration gradients, but are dispersed by turbulent processes [2]. A searcher will encounter odour plumes only ever in an intermittent, transient fashion. The absolute concentration encountered carries little meaning as it is highly variable. The absence of smooth odour gradients has led to the development of navigation algorithms that are driven by odour encounter events, e.g. Infotaxis [3]. Likewise, event-driven navigation algorithms have long been suggested to be the basis of animal behaviour, e.g. odour-gated anemotaxis [4]. In addition, it has been shown that the temporal statistics of odour encounters carry information on source location. In a turbulent environment, a relationship exists between the rate of concentration fluctuations and the distance to the gas source, as shown in wind-tunnel experiments [5], [6], and in the open field [7], [8]. These fluctuations can be captured with off-the-shelf Metal Oxide (MOX) gas sensors, and, when translated into odour-encounter event statistics, allow a prediction of down-wind and cross-wind source distance, independent of absolute odour concentration [9]. It has been shown that MOX sensors could resolve odour encounter events with sub-second precision, which is sufficient to detect the direction of an odour puff in a stereo e-nose setup [10]. This kind of ”stereo-smelling” is crucial to successful source localization [11].

The relevance of event-based statistics inherent to olfactory navigation in turbulent environments motivates a fully event-driven sensing and processing pipeline for robot navigation control. Here, we developed a spiking-network circuit, implemented on SpiNNaker, that can decode odour-puff direction from a pair of enose-systems. This is to our knowledge the first fully event driven neuromorphic system for odour localization. We make three main contributions: 1) A spiking neural network for odour source localization, 2) its implementation on a neuromorphic platform, 3) real-world evaluation with MOX sensors.

II. Hardware and Software

A. Electronic Nose System (enose)

We previously developed an electronic nose system (henceforth called *e-nose*) with four MOX sensors[1] and a high-resolution Analog to Digital Converter (ADC) [10]. Two e-nose boards were used in parallel, controlled by a microcontroller (see Figure 1). One challenge when using MOX sensors to decode rapid odour fluctuations is their slow recovery. Their initial response to an odour pulse is fast, but the slow return of the signal to baseline complicates the detection of fast successive pulses, as new pulses may be masked by remnants of previous odour encounters. The system we used solved this problem by estimating the second derivative of the signal and applying a constant-acceleration Kalman filter to emphasise the onset of odour-encounter events, and de-emphasise trailing recovery [10]. Finally we convert the signal into events by deadband-sampling, where an event is emitted whenever the

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[1]TGS2600, TGS2602, TGS2610 and TGS2620 manufactured by Figaro Inc.

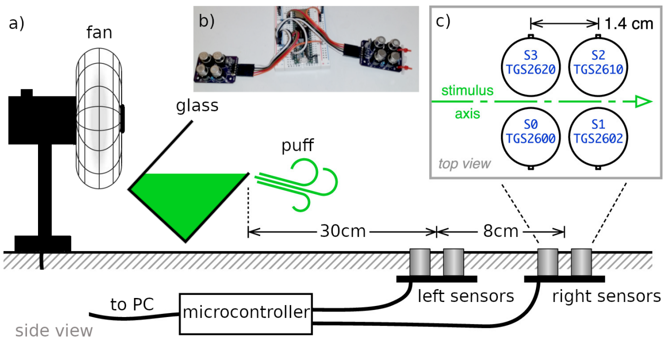

Fig. 1. Sensor setup to detect the direction of the odour puff. a) cartoon of the complete setup. b) real setup. c) MOX sensor array.

signal's change since the last event overcomes a threshold τ. Positive changes are encoded in ON-events while negative changes lead to OFF-events.

B. Spiking Neural Network Architecture (SpiNNaker)

SpiNNaker [1] is a specialized computer architecture featuring massively-parallel multicore computing, ideal for large neural networks. The odour localization network developed in this paper was implemented on a 4-node SpiNNaker machine, which consists of 72 ARM processor cores. It has a $100\,\mathrm{MB\,s^{-1}}$ Ethernet connection for the communication between the computer and the board and two SpiNNaker links. SpiNNaker excels in real-time simulations and maintains power efficiency, closely emulating brain-inspired computation through its neuromorphic hardware.

III. Neural Network

A. Time Difference Encoder (TDE)

The TDE model [12] encodes the time difference between two input events occurring at different input channels in a short burst of output spikes. The time difference is conveyed in the number of spikes as well as the instantaneous firing rate. The model consists of two inputs, the facilitatory gain (fac) and the trigger synapse (trig), as well as one spiking output shown in Figure 2a. Upon the arrival of an event at the facilitatory input, an exponentially decaying facilitatory variable, the gain, is set to its maximum amplitude. The arrival of an event at the trigger synapse shortly after an event at the facilitatory synapse (i.e., small time difference Δt) leads to the generation of an Excitatory Postsynaptic Current (EPSC) (see Fig. 2b). The EPSC amplitude is proportional to the value of the facilitatory variable at the arrival of the trigger event. Hence, the amplitude of the EPSC is inversely proportional to the time difference. A Leaky Integrate and Fire (LIF) neuron integrates the postsynaptic current from the trigger synapse in its Membrane Potential (V_{mem}). A digital output pulse (also called spike) is generated when V_{mem} reaches the spiking threshold θ_{spike}. As it can be seen in Figure 2e, the number of output pulses is inversely proportional to the time difference between the two input events. When the time difference is much longer than the facilitatory time constant, no EPSC is generated and therefore there are no output spikes. For negative time differences (an event occurs at the trigger synapse shortly before an event at the facilitatory input, as in Figure 2d) no output spikes occur. The TDE is a direction-selective module.

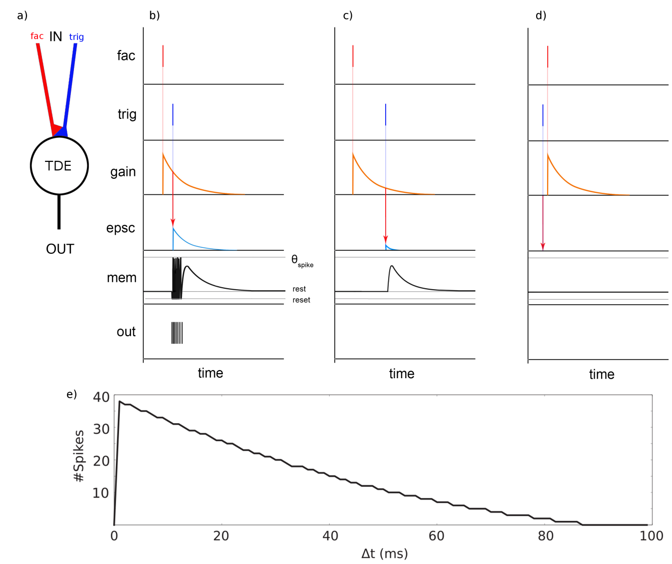

Fig. 2. TDE working principle. a) The TDE consists of a facilitatory and trigger input, a nonlinear gating mechanism and a spiking output. b-d) response to different input event combinations. e) Tuning curve. Figure adapted from [13].

B. Odour localization network

The odour localization network is depicted in Fig. 3. It consists of three layers, namely the sensor events input, an onset filter layer and a TDE layer. While the TDE model is described in detail in the previous section all other layers consist of exponential Leaky Integrate and Fire (LIF) neurons. The left and right neuron of the sensor events layer receive events from the left and right gas sensors, respectively. The conversion from analog sensory signal to events is explained in subsection II-A in detail. The sensor events layer is used to read out the events received by the SpiNNaker board. It projects one-to-one onto the neurons of the onset filter layer. The appearance of an odour puff at the sensor generates a large number of successive output events with a high firing rate. However, we aim to detect the time difference between the arrival of the odour plume at the two sensors. One reliable way to extract the time difference from these event trains is to extract the onset of the signal. We achieve this by a recurrent inhibitory connection in the onset filter layer. The occurrence of the first spike in the onset filter neuron leads to strong self inhibition of the neuron. The excitation by the successive sensor event spikes is not strong enough to overcome the inhibition so that the onset layer only passes on the first spike caused by the arrival of an odour plume. The output spikes of the onset filter are passed on to two TDEs, one right-left connected and the other left-right connected. The first responds to a movement of an odour plume from right to left while the

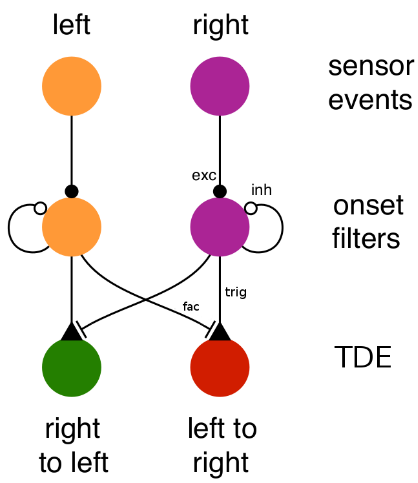

Fig. 3. Odour localization network. The sensor events layer passes on the events, the onset filter only outputs the first spike of a spike train, TDEs estimate the time difference.

latter responds to a plume moving in the opposite direction. Thus, the network was developed to detect the location of the odour source by determining the spatio-temporal occurrence of the odour plume.

IV. Experiments and Results

The sensory setup shown in Fig. 1 was placed approximately 30 centimeters away from a small fan. Short puffs of a lime mixture were manually provided to the fan. The experiment was repeated 8 times with the fan being placed on the right side of the sensors and on the left side, respectively. On a computer the recorded continuous analog signals were converted to spike trains with the method explained in subsection II-A. The spike trains were passed to a SpiNN-3 board which contained the Spiking Neural Network (SNN) explained in subsection III-B. An example conversion from continuous sensory signal to events is shown in Fig. 4. Every sensor board had four different MOX sensors which reacted to different gas molecules. Sensor $S1_L$ and sensor $S1_R$ were sensitive to the lime molecules provided (See Fig. 4a). From second 7.5 until second 10 the two orange sensory signals were rising to their resting potential. The sensors were still recovering from a previous odour puff. Around second 11 a new odour puff moved over the two sensors from the right to the left. This lead to a slow decrease in voltage in sensor $S1_R$ and $S1_L$. After second 12 the sensors began to recover again. The Kalman filter's second derivative of the sensory signals is shown in Figure 4b. The transients during the occurrence of an odour puff were much steeper and faster than the original sensory signals. The on and off events of the channels are shown in red and blue respectively.

We project the extracted off events onto the odour detection network implemented on a SpiNN-3 board. The results are provided in Figure 5. The two bottom rows of each trial show the sensor events, the two rows above show the onset

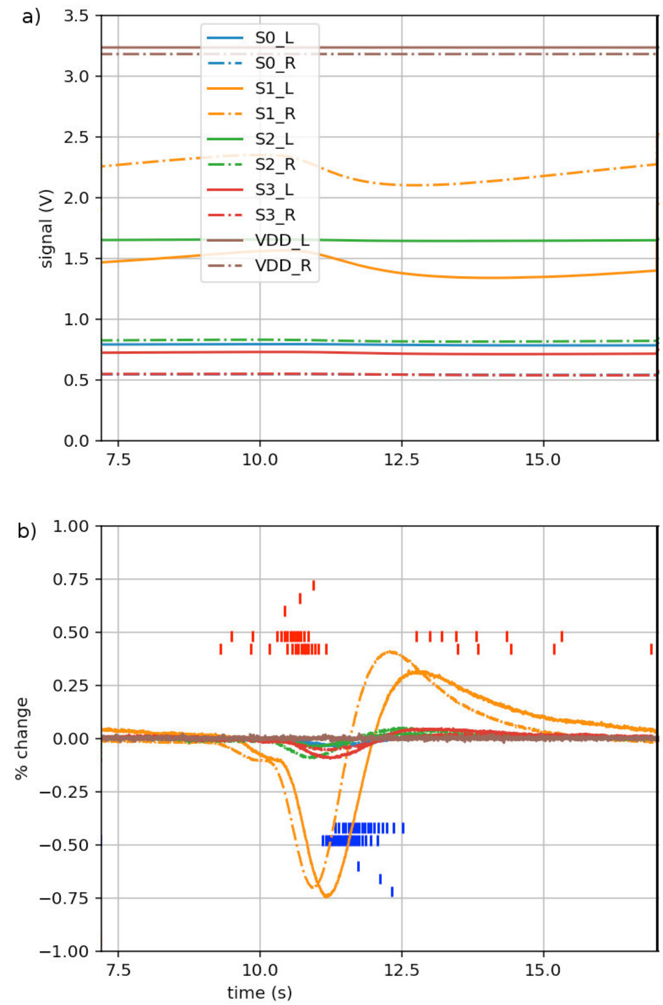

Fig. 4. Conversion from sensory signals to events.a) raw signals of the four different MOX sensors. b) Kalman filtered second derivative of sensory signals as well as event signals (red and blue).

filters and the two top rows show the TDEs. In all 16 trials the network correctly determined the direction of the odour bout. The network performs robustly in a large range of time-differences ranging from below 0.05 to 0.24 seconds (Fig. 5 right to left trial 7 and left to right trial 2)

V. Conclusions

We have shown a fully event-driven neuromorphic processing pipeline that can decode the direction of an odour puff with a stereo e-nose setup. The core component of this network is the TDE model. The applicability of the TDE for temporal encoding in vision, touch and sound has already been demonstrated in [12]–[16] and [17]. In this article we utilize the TDE in the odour domain. The versatile applicability of the TDE concept suggests the presence of a similar mechanism in different animal species and across different sensory domains. Furthermore, due to its versatile applicability we suggest to use the TDE as a basic sensory filtering mechanism in the neuromorphic domain. The TDE works especially well in

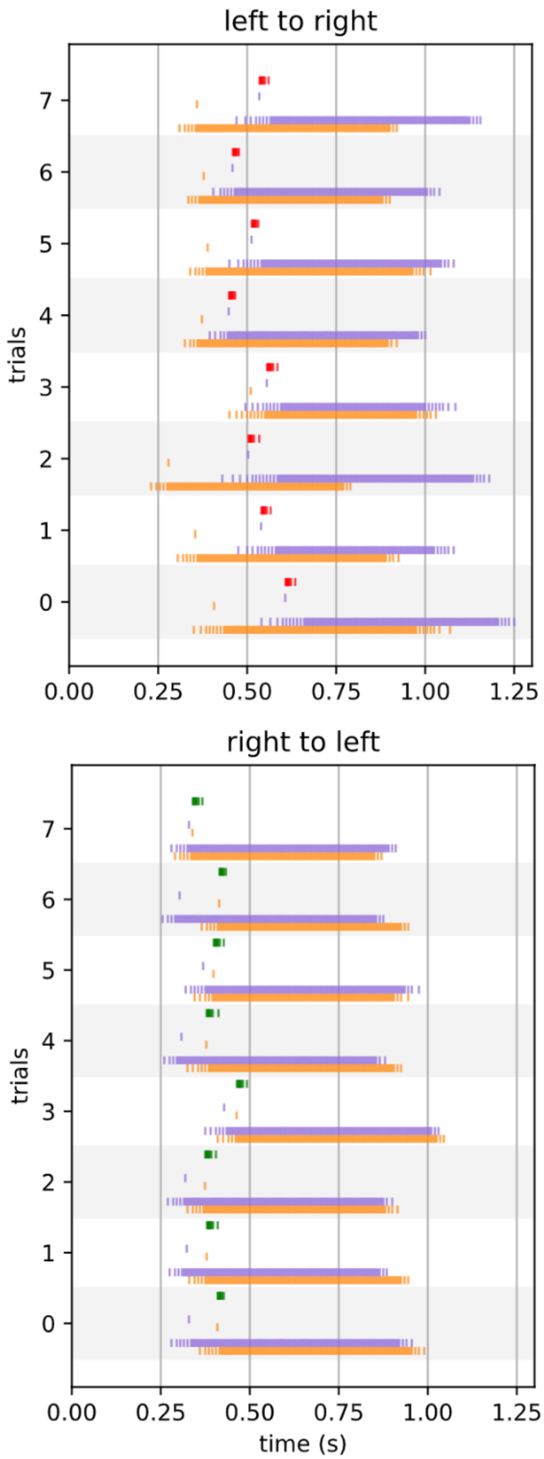

Fig. 5. Network response to a puff of odour coming from the left or right. Bottom row orange and purple: Raw events from the e-nose sensor. Top row orange and purple: onset filter spikes. Red and green: TDE spikes left to right and right to left respectively. A single puff of odour causes a large amount of successive events from the sensor. The onset filter reduces these events to a single spike per channel at the onset of the puff. The onset filter spikes project onto the TDEs. A stimulus moving from left to right causes a response of the left to right TDE (red) while a stimulus moving from right to left causes a response of the opposite TDE (green).

combination with event based sensors because these sensors provide precise temporal information in their time-continuous output. In this article the slow dynamics of the MOX sensors had first to be overcome by estimating the second derivative of the sensory signal and applying a constant-acceleration Kalman filter. This accelerated gas sensing approach can also support olfactory scene recognition in natural environments such as urban cityscapes [18]. Spiking networks are compatible with this approach [19]. In a future implementation of our approach on a robotic platform we will investigate its performance regarding odour-gated anemotaxis for robots.

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