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Concentration normalization with a model of gain control in the olfactory bulb

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Abstract

This article presents a biologically inspired model capable of removing concentration effects from the multivariate response of a gas sensor array. The model is based on the first stage of lateral inhibition in the olfactory bulb, which is mediated by periglomerular interneurons. To simulate inputs to the olfactory bulb, signals from a chemosensor array are first processed with a self-organizing model of chemotopic convergence proposed earlier, which leads to odor-specific spatial patterning. Subsequently, a shunting lateral inhibitory network, modeled after the role of periglomerular cells in the olfactory bulb, is used to compress concentration information. The model is validated using experimental data from an array of temperature-modulated metal-oxide chemoresistors.

Keywords: Biologically inspired signal processing; Machine olfaction; Temperature modulation; Self-organized maps; Lateral inhibition

1. Introduction

The input to the olfactory bulb is characterized by massive convergence of olfactory receptor neuron (ORN) axons expressing the same receptor gene onto a single or few target glomeruli [1]. This chemotopic convergence creates compact odor maps that decouple odor quality from intensity. The encoded intensity information at this early stage is transformed by a layer of lateral inhibitory circuits driven by periglomerular interneurons (PG cells). These lateral interactions are known to be of a shunting type (divisive inhibition), and have been hypothesized to serve as a "volume control" mechanism [2], enabling identification of odorants over several log units of concentration. Recently, these glomerular circuits have been found to have center-surround connectivity, and have been suggested to perform pattern normalization, low-band filtration and contrast enhancement [3]. Following these "volume control" circuits, odor signals are further sharpened by another stage of lateral inhibition at the output of the olfactory bulb, mediated by granule cells [4]. The resulting odor signals are then stored in the cortex for subsequent recognition.

Inspired by advances in our understanding of the key processing principles in the olfactory pathway, neuromorphic models for chemical sensor arrays have become a subject of attention in recent years. Ratton et al. [5] employed the olfactory model of Ambros-Ingerson et al. [6], which simulates the closed-loop interactions between the olfactory bulb and higher cortical areas. The model performs a hierarchical processing of an input stimulus into increasingly finer descriptions by repetitive projection of bulbar activity to (and feedback from) the olfactory cortex. Ratton et al. applied the model to classify data from a micro-hotplate metal-oxide sensor excited with a saw-tooth temperature profile. Sensor data was converted into a binary representation by means of thermometer and Gray coding, which was then used to simulate the spatial activity at the olfactory bulb. Their results showed that classical approaches (Gram-Schmidt orthogonalization, fast Fourier transform and Haar wavelets) yield better classification performance. This result should come as no surprise given that the thermometer and Gray codes are unable to faithfully simulate the spatial activity at the olfactory bulb, where the most critical representation of an odor stimulus is formed.

White et al. [7,8] employed a spiking neuron model of the peripheral olfactory system to process signals from fiber-optic sensor array. In their model, the response of each sensor is converted into a pattern of spikes across a population of ORNs,

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which then projects to a unique mitral cell. Different odors produce unique spatio-temporal activation patterns across mitral cells, which are then discriminated with a delay line neural network (DLNN). Their OB-DLNN model is able to produce a decoupled odor code: odor quality being encoded by the spatial activity across units, and odor intensity by the response latency of the units.

Pearce et al. [9] investigated the issue of concentration hyperacuity by means of massive convergence of ORNs onto GL. Modeling spike trains of individual ORNs as Poisson processes, the authors show that an enhancement in sensitivity by a factor of $\sqrt{n}$ can be achieved at the GL, where n is the number of convergent ORNs. Experimental results on an array of optical micro-beads are presented to validate the theoretical predictions.

Otto et al. employed the KIII model of Freeman et al. [10] to process data from FT-IR spectra [11,12] and chemical sensors [13]. The KIII is a neurodynamics model that faithfully captures the spatio-temporal activity in the olfactory bulb, as observed in electro-encephalogram (EEG) recordings. In [11], the FT-IR spectrum of each analyte was decimated, Hadamard-transformed and normalized before being used as an input vector into the KIII model. The authors showed that the principal components of the mitral cell state-space attractors can be used to discriminate different analytes. Their results, however, indicated that the KIII is unable to match the performance of a regularized discriminant analysis classifier.

Gutierrez-Osuna et al. [14,15] investigated the use of habituation for processing odor mixtures with chemical sensor arrays. A statistical pattern recognition model was presented in [14], where habituation is triggered by a global cortical feedback signal, in a manner akin to Li and Hertz [16]. A neuromorphic approach based on the KIII model was proposed in [15], where habituation is simulated by local synaptic depression of mitral channels. Inspired by the role of GL as functional units [17], sensor array patterns are preprocessed with a family of odor selective discriminant functions before being fed to the KIII model. Their results showed that Hebbian pattern-completion allows the KIII model to recover the majority of the errors, which were introduced in the sensor array and discriminant function stages.

To the best of our knowledge, however, the role of lateral inhibition mediated by PG cells has not been explored for the purpose of processing multivariate signals from chemical sensor arrays. In this paper, we propose a computational model of these gain-control circuits in the olfactory bulb, and analyze its suitability to perform concentration normalization. The model is validated on experimental data from an array of temperature-modulated metal-oxide gas sensors.

2. Proposed model

A fundamental difference between machine and biological olfaction is the dimensionality of the input space. The biological olfactory system employs a large population of ORNs, e.g. 100 million neurons in the human olfactory epithelium, replicated from 1000 primary receptor types [18], whereas its artificial analogue uses very few sensors. In order to narrow this dimensionality gap, we make use of the temperature-selectivity dependence of metal-oxide (MOS) materials [19]. Specifically, we modulate the operating temperature of a MOS sensor with a slow (mHz) sinusoidal waveform, and treat the sensor response at each temperature set point as a "pseudo-sensor," as illustrated in Fig. 1.

To model the chemotopic convergence of ORNs onto glomeruli, we perform a topological clustering of the resulting pseudo-sensors according to their selectivity [20,21]. Formally, we define the selectivity of a pseudo-sensor by its response across a set of Q volatile compounds:

$$\mathrm{ORN}_i = [\mathrm{ORN}_i^{\mathrm{O}_1}, \mathrm{ORN}_i^{\mathrm{O}_2}, \ldots, \mathrm{ORN}_i^{\mathrm{O}_Q}] \quad (1)$$

where $\mathrm{ORN}_i^{\mathrm{O}}$ is the response of ORN_i to odor O, and Q is the number of odorants. We will refer to this Q-dimensional space as the affinity space.

Since GLs are arranged as a single layer in the olfactory bulb, and given that neighboring GL tend to respond to similar odors [22,23], a natural choice to model the ORN-GL convergence is the self-organizing map (SOM) of Kohonen [24]. After training, the distribution of SOM nodes will follow the probability density function of pseudo-sensors in affinity space. Each pseudo-sensor can then be assigned to the closest SOM node (a virtual glomerular unit), thereby forming a convergence map

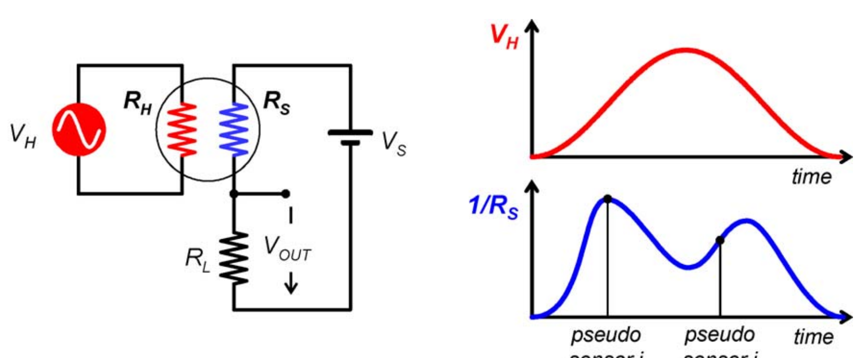

Fig. 1. Temperature modulation for metal-oxide sensors. A sinusoidal voltage V_{H} is applied to a resistive heather R_{H}, and the sensor resistance R_{S} is measured as a voltage drop across a load resistor R_{L} on a half-bridge. Due to the temperature-selectivity dependence, the response of a sensor at a particular temperature can be treated as a separate "pseudo-sensor," and used to simulate a large population of ORNs.