Habituation in the KIII olfactory model using gas sensor arrays

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Inspired by the habituation process in the olfactory system, this article presents an approach for analyzing electronic-nose data using Freeman's KIII neurodynamics model. In order to ensure the additivity of patterns from odor mixtures, input data from a gas sensor array is first processed with a family of discriminant functions that yield an orthogonal binary representation. The process of habituation is then simulated through synaptic depression with a decay term that reduces the strength of mitral and granule connections when the KIII model is excited with a continuous stimulus. As a result, the system is able to mimic the effects of habituation when processing odor mixtures with gas sensor arrays.

1 Introduction

Habituation is a process that allows a sensory system to reduce its sensitivity to previously detected stimuli, preventing sensory overflow in the central nervous system and improving the ability to detect new, and potentially more informative, stimuli. Such remarkable capability has great potential in the field of machine olfaction to help remove background analytes (e.g., matrix effects) and enhance the selectivity of the system towards the interesting components in a given chemical detection problem. To the best of our knowledge, however, no publications have addressed the issue of habituation in the context of gas sensor array processing.

The goal of this work is to study the feasibility of the habituation process in gas sensor arrays using a non-linear dynamic model of the olfactory system. Depicted in Figure 1(left), the computational model employed in this article is the KIII dynamic system developed by Freeman and colleagues over the past three decades [1]. The KIII is a system of second-order non-linear differential equations that simulates the chaotic activity of neuron populations, as observed in electro-encephalogram (EEG) recordings. At the core of the model is a bank of coupled oscillators, called KII sets, containing one or two pairs of mitral-granule cells. The KIII receives inputs from a layer of receptors (or glomeruli), as well as feedback from two additional KII sets that represent the anterior olfactory nucleus and prepyriform cortex. The KIII works as an associative memory; it can be trained to recognize different patterns and is also capable of recovering incomplete patterns.

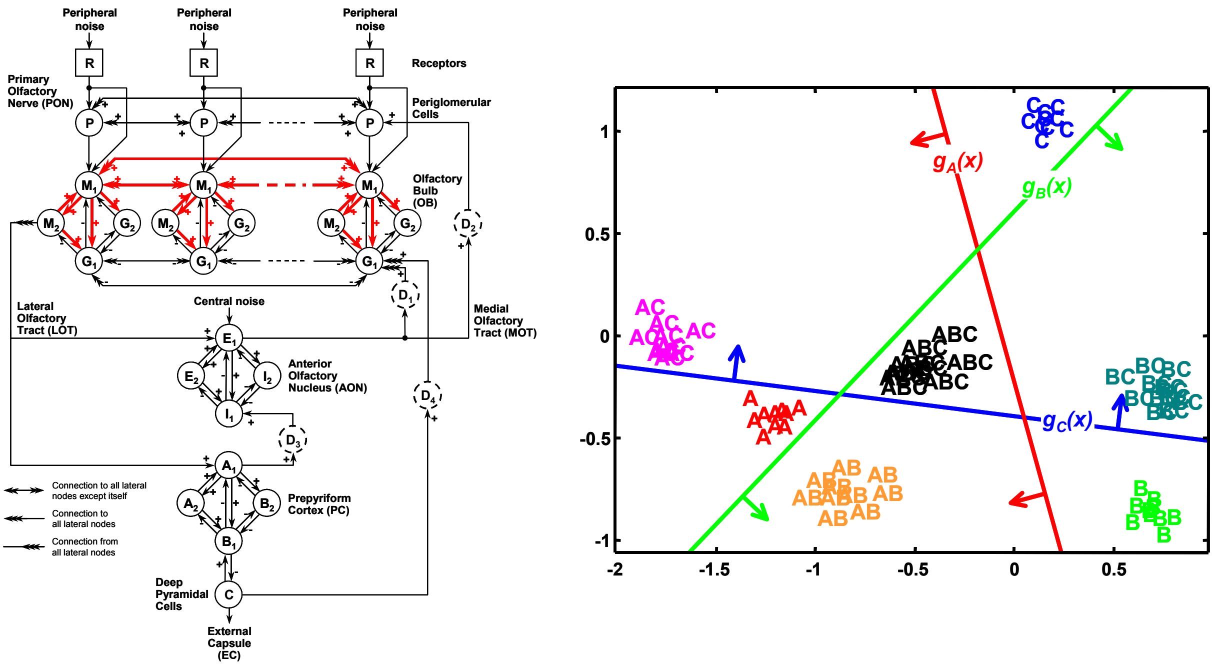

Figure 1. Architecture of Freeman's KIII model (left). Odor-selective separating hyperplanes (right)

2 Odor-selective separating hyperplanes

As in other types of associative memory, a critical requirement in the KIII model is that input patterns be minimally overlapping. Moreover, in order to facilitate the processing of odor mixtures, it is also important that input patterns be additive. These constraints are in apparent contradiction with the behavior of most electronic-nose sensors. For these reasons, sensor patterns x are first passed through a family of discriminant functions $g_c(x)$ that dissects feature space into odor-specific regions. This process is illustrated in Figure 1(right) for a two-dimensional classification problem with three odors and their corresponding mixtures. Each odor-specific discriminant function divides feature space into two decision regions, with the arrows indicating the region where mixture patterns containing the odor of interest are located. Therefore, each of these discriminant functions can be thought of as a very selective pseudo-sensor capable of detecting the presence of a particular odor that may be embedded in a background or a mixture. The outputs of this family of discriminant functions serve as input channels to the KIII model. Multiple families (or feature spaces) can be extracted for a particular sensor array by considering different preprocessing techniques, feature subsets or operating temperatures.

Two procedures are commonly employed to compute this type of linear discriminant functions: perceptron learning and minimum squared-error (MSE) regression. The perceptron learning rule finds a solution if the problem is linearly separable, but fails to converge on non-separable problems. The MSE procedure, on the other hand, does not have convergence problems but is not guaranteed to find a solution for linearly separable patterns. To avoid the shortcomings of either method, we employ an iterative algorithm known as the Ho-Kashyap procedure [2], which is guaranteed to converge and find a solution if the problem is linearly separable, as illustrated in Figure 1.

3 Habituation in the KIII model

It is generally accepted that the neural basis for habituation is depression of synaptic connections [3]. In the KIII this can be modeled by introducing a decay term that reduces the strength of all the positive weights in the olfactory bulb –those highlighted in Figure 1(left), which connect mitral cells to other neurons in the bank of KII sets [4]

$$w(t+\Delta t) = \big(w(t) - B\big)\exp\left[-\Delta t / \tau\right] + B \qquad (1)$$

where $w=(w_{GM}, w_{MM})$, B is the strength of the connection under complete habituation, and τ is a time constant governing the rate of habituation. This habituation process is triggered locally on each KII set when the amplitude of its mitral and granule cell oscillations exceeds a threshold value. Dishabituation is simulated in a similar fashion.

Experimental results of this habituation process are illustrated in Figure 2 for a KIII system trained on a classification task with two odors: A [10010010] and B [01001001]. The first three columns in the figure represent the response of the KIII (G_2 channels) to patterns A, B and A∪B. The remaining two columns illustrate the effect of habituation in a mixture-processing scenario. In Figure 2(d), the KIII is initially excited with input A and allowed to habituate. As a result, the amplitude of the channels encoding for that odor is reduced over time. When the mixture A∪B is introduced after habituation to A, the KIII generates an oscillatory pattern similar to that of odor B alone. Figure 2(e) illustrates the opposite scenario, in which the KIII is able to adapt to odor B. Qualitatively similar results are also obtained when the input patterns fail to be orthogonal, a situation that occurs when the decision regions described in section 2 are not linearly separable. These results indicate that the proposed algorithms represent a valid approach for the study of habituation in gas sensor array systems.

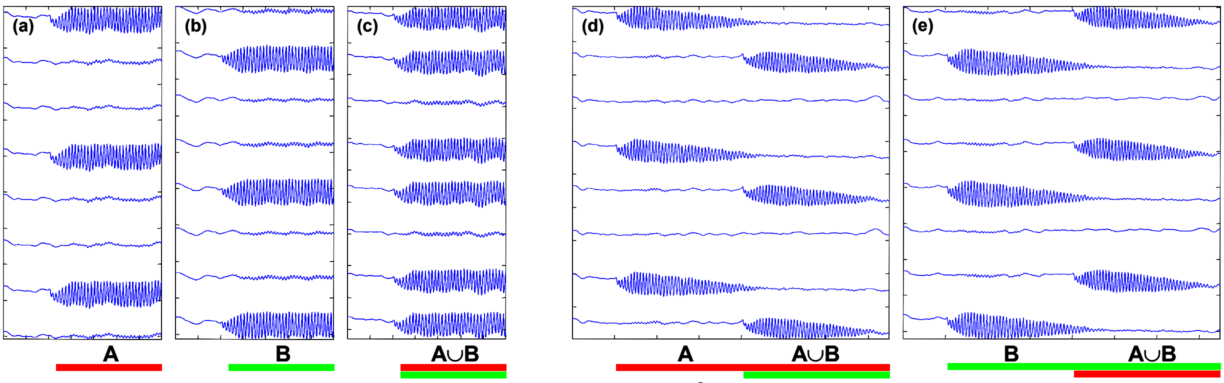

Figure 2. Response of the KIII model to odors A, B and AÈB before (a-c) and after habituation (d-e)

4 Acknowledgments

This research was supported by award from NSF/CAREER 9984426. We are grateful to Nilesh Powar for his assistance with data collection.

5 References

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