Pattern recognition for chemosensor arrays with the KIII model

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Abstract- This article presents an overview of on-going research with the KIII as a pattern recognition model for chemical sensors arrays. Two different input representations are investigated: binary and continuous patterns. Binary inputs are obtained by partitioning feature space into odor-selective regions. This representation allows inputs to be viewed as 'labeled lines,' the functional role of glomerular units in olfactory processing. In addition, we also explore the behavior of the KIII when driven by continuous sensor data. Preliminary results show that hebbian learning in the continuous-input KIII improves the discrimination of odor attractors.

1 Introduction

Sensor based machine olfaction (SBMO) has emerged in the past two decades as an alternative methodology for the measurement of volatile organic compounds (VOCs), a task traditionally performed with analytical techniques, such as gas chromatography and mass spectrometry, or sensory analysis with human panels. SBMO employs an array of broadly-tuned chemical sensors: exposure of the sensors to a VOC produces a unique multivariate pattern across the array, which can then be processed with pattern recognition techniques to determine the identity and/or concentration of the VOC.

Statistical pattern recognition and artificial neural networks have been well studied in the machine olfaction literature [1]. Hence, our research interests have concentrated on biologically-plausible models of olfactory processing [2], as these models provide an opportunity for formulating new computational problems worthy of study with chemical sensor arrays (e.g., habituation, segmentation, background suppression). Among the wealth of olfactory models, the KIII [3] is particularly attractive for chemosensor data because, as a dynamic model of neuronal populations, it strikes a balance between anatomical realism (e.g., Hodgkin-Huxley) and functional abstraction (e.g., perceptron). In addition, the KIII has been extensively studied by Freeman and colleagues [4] over the course of three decades.

2 Binary KIII and mixture processing

Inputs to the KIII are generated from the response patterns of an array of metal-oxide chemoresistors. The selectivity of a metal-oxide sensor is a function of its operating temperature (~400ºC), which is controlled with a built-in heater. The overall selectivity can thus be improved by capturing the sensor response at multiple heater voltages, a principle known as temperature modulation [5].

Although the KIII can be stimulated directly with raw sensor data, our earlier work has employed a preprocessing stage that yield a more suitable orthogonal binary representation. The solution consists of partitioning feature space into odor-selective regions, as depicted in Fig. 1(a) for a 2D classification problem with three odors and their corresponding mixtures. A linear discriminant function (LDF) is used to divide feature space into two decision regions, with the arrows indicating those mixture patterns (e.g., AC) that contain a single odor (e.g., A). Therefore, each of these LDFs 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 complex background.

We have employed this binary representation to simulate olfactory habituation, a process by which the system can reduce its sensitivity to previously detected odors, thereby improving the ability to detect new stimuli. This process is implemented by synaptic depression of mitral (M) connections triggered by local activity [6]. Fig. 1(b) shows the response of an 8-channel KIII to individual patterns of odors A, C and the mixture AC. Habituation is disabled to illustrate the additivity of patterns and steady-state response. Fig. 1(c) illustrates the effect of habituation: the system is initially presented with odor A and allowed to habituate. At this time, binary mixture AC is introduced. As shown in the figure, the response to AC is as if only C was present, reproducing a known olfactory perception phenomenon. Our results [6] also

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show that the pattern-completion role of the hebbian M-M connections allows the KIII to reduce the majority of the coding errors introduced by the LDF, from an error rate of 6.25% down to 0.69%.

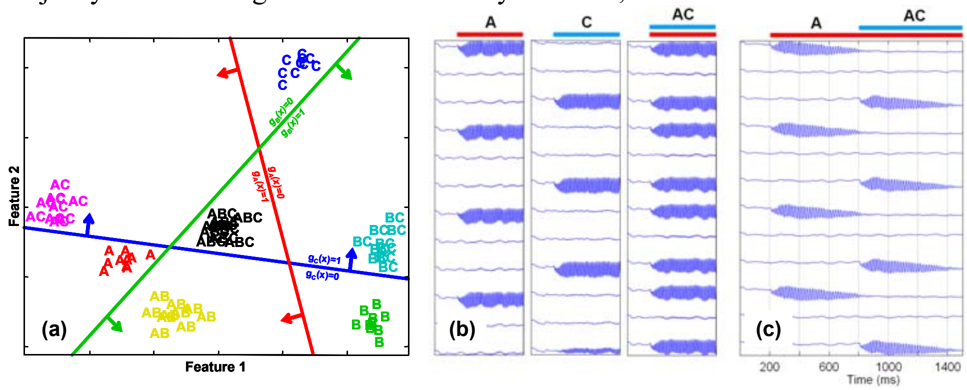

Fig. 1. (a) Partitioning of feature space into odor-selective regions: acetone (A), isopropyl alcohol (B) and ammonia (C). (b) G2 output patterns of the KIII without habituation. (c) Habituation process with odors A and AC.

3 Processing of continuous inputs

The use of continuous inputs is appealing because it allows the KIII to process raw sensor data without any preprocessing. In addition, continuous inputs preserve concentration information (input amplitude), which is lost in the previous binary representation. The pattern classification capabilities of the KIII with continuous inputs have not been investigated as extensively as with binary patterns. However, such efforts have already shown promising results [4, 7].

We have studied the performance of continuous inputs on a 64-channel KIII model. Each input was fed with a feature from a 64-dimensional vector containing the response of the sensor array to one of three analytes: acetone, isopropyl alcohol and ammonia. The KIII was initialized with uniform M-M connections, which were then allowed to undergo Hebbian learning with repeated presentation of the analytes. The activity of G1 nodes was used as an output, and the 64-dimensional dynamic attractor was projected onto the three largest principal components for visualization purposes. Fig. 2(a) and (b) show the response of the KIII prior to and after learning, respectively. Before learning, the three analytes lead to very similar, nearly coplanar attractors. Following learning, the attractors change drastically, improving the discrimination of the three analytes. Though preliminary, these results show promise for real-time odor detection with hardware implementations of the KIII model.

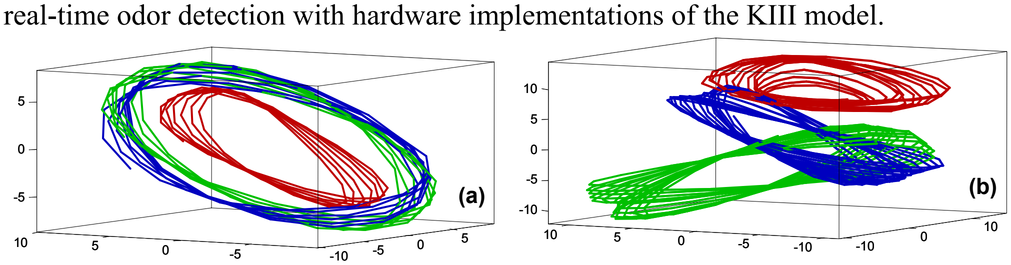

Fig. 2. KIII response for three odors before (a) and after Hebbian learning (b).

4 References

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