REFERENCES

[1] M. A. Cohen and S. Grossberg, "Absolute stability and global pattern formation and parallel memory storage by competitive neural networks," *IEEE Trans. Syst. Man Cybern.*, vol. 13, pp. 815–821, Sept. 1983.

[2] X. B. Ling and L. D. Wu, "Global exponential stability of a class of neural circuits," *IEEE Trans. Circuits Syst. I*, vol. 46, pp. 748–751, June 1999.

[3] D. G. Kelly, "Stability in constractive nonlinear neural networks," *IEEE Trans. Biomed. Eng.*, vol. 37, pp. 231–242, Mar. 1990.

[4] K. Matsuoka, "Stability conditions for nonlinear continuous neural networks with asymmetric connection weights," *Neural Networks*, vol. 5, pp. 495–500, Sept. 1992.

[5] E. Kaszkurewicz and A. Bhaya, "Comments on necessary and sufficient condition for absolute stability of neural networks," *IEEE Trans. Circuits Syst. I*, vol. 42, pp. 497–499, Aug. 1995.

[6] Y. Fang and T. G. Kincaid, "Stability analysis of dynamical neural networks," *IEEE Trans. Neural Networks*, vol. 7, pp. 996–1005, July 1996.

[7] H. Yang and T. S. Dillon, "Exponential stability and oscillation of Hopfield graded response neural networks," *IEEE Trans. Neural Networks*, vol. 5, pp. 719–729, Sept. 1994.

[8] M. Forti and A. Tesi, "New conditions for global stability of neural networks with application to linear and quadratic programming problems," *IEEE Trans. Circuits Syst. I*, vol. 42, pp. 354–366, July 1995.

[9] C. Hou and J. Qian, "Stability analysis for neural dynamics with time varying delays," *IEEE Trans. Neural Networks*, vol. 9, pp. 221–223, Jan. 1998.

[10] K. Gopalsamy, *Stability and Oscillations in Delay Differential Equations of Population Dynamics*. Dordrecht, The Netherlands: Kluwer Academic, 1992.

[11] K. Gopalsamy and X. He, "Delay-independent stability in bidirectional associative memory networks," *IEEE Trans. Neural Networks*, vol. 5, pp. 998–1002, Nov. 1994.

[12] J. J. Hopfield, "Neural networks and physical systems with emergent collective computational abilities," *Proc. Nat. Acad. Sci. USA*, vol. 79, pp. 1554–1558, 1984.

[13] B. Kosko, *Neural Networks and Fuzzy Systems—a Dynamical Systems Approach to Machine Intelligence*. New Delhi, India: Prentice-Hall of India, 1994.

[14] ——, "Bidirectional associative memories," *IEEE Trans. Syst. Man Cybern.*, vol. 18, pp. 49–60, Jan. 1988.

[15] ——, "Unsupervised learning in noise," *IEEE Trans. Neural Networks*, vol. 1, pp. 44–57, Mar. 1990.

[16] P. K. Simpson, *Artificial Neural Systems—Foundations, Paradigms, Applications and Implementations*. New York: Pergamon Press, 1989.

[17] V. Sree Hari Rao, B. R. M. Phaneendra, and V. Prameela, "Global dynamics of bidirectional associative memory networks with transmission delays," *Differential Equations and Dynamical Syst.*, vol. 4, pp. 453–471, 1996.

[18] V. Sree Hari Rao and B. R. M. Phaneendra, "Global dynamics of bidirectional associative memory neural networks involving transmission delays and dead zones," *Neural Networks*, vol. 12, pp. 455–465, Apr. 1999.

Habituation in the KIII Olfactory Model With Chemical Sensor Arrays

Ricardo Gutierrez-Osuna and Agustin Gutierrez-Galvez

***Abstract*—This paper presents a novel combination of chemical sensors and the KIII model for simulating mixture perception with a habituation process triggered by local activity. Stimuli are generated by partitioning feature space with labeled lines. Pattern completion is demonstrated through coherent oscillations across granule populations using experimental odor mixtures.**

***Index Terms*—Chemical sensors, coherent oscillations, KIII model, labeled lines, olfactory habituation.**

I. 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, therefore, more informative stimuli. This computational function has great potential in sensor-based machine olfaction [1] as a mechanism to reduce the effect of background odors and enhance selectivity toward the interesting components in a sample. However, with the exception of our own prior work, the issue of habituation has not been explored in the context of chemical sensor arrays.

Wang *et al.* [2] have proposed a mechanism for the related problem of pattern segmentation. Alternating bursts of activity induced by self-inhibition are used to create a spatiotemporal pattern that sequentially extracts the components of a mixture. Hendin *et al.* [3] have studied odor segmentation as a blind-source separation problem where the different components in an odor mixture follow independent temporal fluctuations. Li and Hertz [4] have proposed a feedback mechanism for odor segmentation whereby the olfactory bulb activity is modulated with an efferent signal after an odor is recognized. In [5] we have presented a statistical pattern recognition approach for odor segmentation with chemical sensor arrays where habituation is triggered by a central feedback signal, in a manner akin to Li and Hertz [4].

In contrast to our prior work, the objective of this paper is to investigate the habituation process using: 1) a biologically plausible computational model and 2) an adaptation mechanism based on local activity. In the process, we also explore the pattern-completion capabilities of the KIII model when processing experimental sensor data. To simulate olfactory stimuli, the KIII model is connected to an array of temperature-modulated chemoresistors. In order to produce an olfactory code consistent with the widely accepted role of glomeruli as functional units [6], the sensor-array feature space is partitioned into odor-selective regions by means of a family of linear discriminant functions. This ensures that, under habituation to one of the components in a mixture, the system is able to shift the perceived quality toward the remaining components in the mixture, as observed in sensory analysis [7]. The complete system is evaluated on a series of habituation scenarios in the context of odor mixture processing.

Manuscript received November 6, 2002; revised March 18, 2003. This work was supported by the NSF CAREER Grant 9984426/0229598.

The authors are with the Department of Computer Science, Texas A&M University, College Station, TX 77843 USA (e-mail: rgutier@cs.tamu.edu; agustin@cs.tamu.edu).

Digital Object Identifier 10.1109/TNN.2003.820438

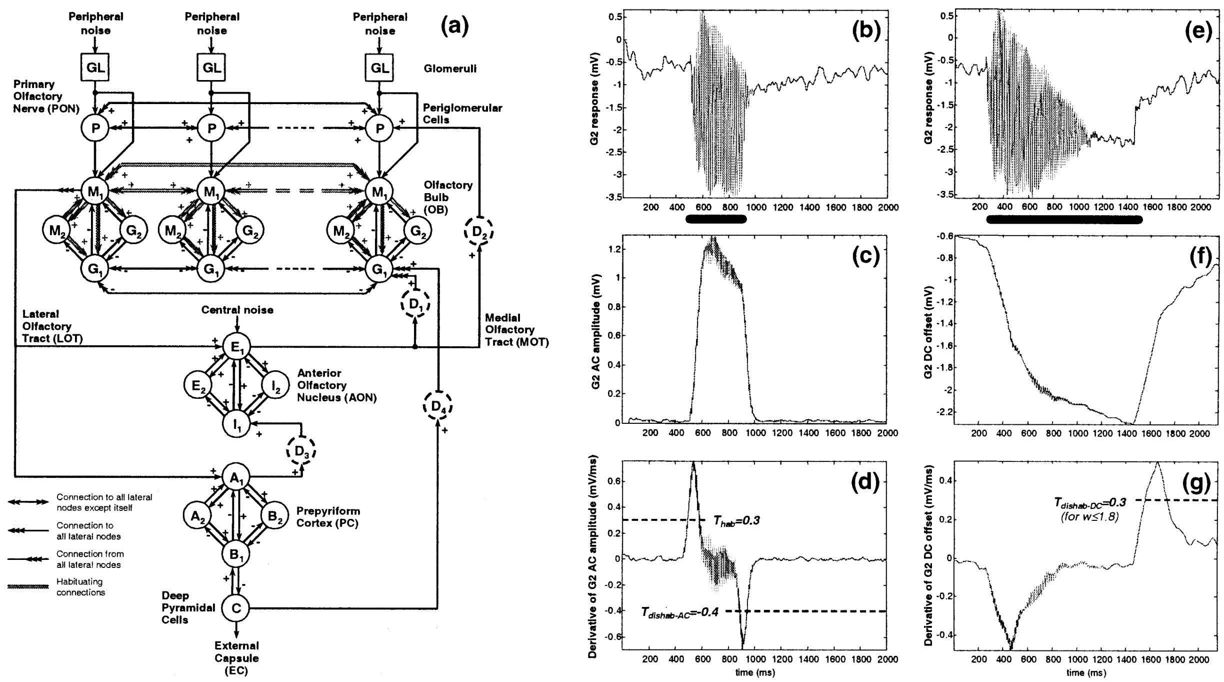

Fig. 1. (a) Habituation in the KIII model [10] affects mitral connections. Triggering habituation and dishabituation from G2 activity: (b)–(d) stimulus is removed before and (e)–(g) after full habituation.

II. The KIII Model

The KIII model is a system of second-order nonlinear differential equations that simulates the chaotic activity of neuron populations, as observed in electroencephalogram recordings. As shown in Fig. 1(a), the core of the model consists of a bank of coupled oscillators, called KII sets, representing two pairs of mitral and granule populations. Each one of these banks is connected to a periglomerular node, from which receptor stimuli are fed into the system. The KIII receives feedback from two additional KII sets that represent the anterior olfactory nucleus and prepyriform cortex, allowing the system to display pseudochaotic dynamics behavior, as opposed to limit cycles. Odor stimuli at the receptor layer change the dynamics of the system, which is commonly analyzed through the oscillatory patterns of mitral or granule cells. Interaction between neuron populations are regulated with connection weights, most of which are fixed to ensure proper dynamic behavior. The only exception corresponds to mitral-to-mitral connections, which undergo Hebbian learning, allowing the KIII to serve as an associative memory.

A. Habituation in the KIII Model

Following Kozma and Freeman [9], the habituation process is assumed to induce depression of the connections from mitral nodes onto other neuron populations, as highlighted in Fig. 1(a). Changes in these connections are proportional to their instantaneous value and, thus, follow an exponential decay [8]:

$$\Delta w = w(t+\Delta t) - w(t) = [B - w(t)]\left[1 - \exp\left(-\frac{\Delta t}{\tau}\right)\right] \quad (1)$$

where w represents a connection from the habituating mitral cell onto other mitral or granule cells, τ is a time constant governing the rate of habituation, and B is the final value that the connection will approach asymptotically. A value of $\tau = 500$ ms is used in this work.[1] During the habituation process, B is the minimum strength of the connection (i.e., under complete habituation.) A suitable value of $B = 1.5$ was obtained through experimentation.[2] Under dishabituation, B is simply the original value of the connection which, along with all remaining fixed parameters[3] and KIII model, is borrowed from [10].

In contrast with the mechanism of Kozma and Freeman [9], in which a node undergoes habituation if it exceeds the average activity across the mitral layer, our habituation/dishabituation processes are initiated based solely on the local activity at each channel (for biological plausibility purposes.) Our triggers are illustrated in Fig. 1(b) through (g). Following [11], the ac activity at each G2 node $(G2_{\mathrm{ac}})$ is computed with a 50 ms-wide moving window. The window is split into 10 nonoverlapping segments, and the average of the standard deviation at each segment is used as a measure of ac amplitude [see Fig. 1(c)]. From the derivative of $G2_{\mathrm{ac}}$ [see Fig. 1(d)], suitable thresholds $T_{\mathrm{hab}} = 0.3$ mV/ms and $T_{\mathrm{dishab-ac}} = -0.4$ mV/ms are then used to detect the onset of habituation and dishabituation, respectively. The threshold $T_{\mathrm{dishab-ac}}$ works as long as the stimulus is removed before full habituation is reached. Otherwise, the ac amplitude cannot be discriminated from the basal state, as illustrated in Fig. 1(e). In this case, a sudden change in dc offset can be used to detect that the stimulus has been removed. The dc component of each G2 node $(G2_{\mathrm{dc}})$, shown in Fig. 1(f), is computed with a 200-ms causal moving average. A threshold $T_{\mathrm{dishab-dc}} = 0.3$ mV/ms is then applied to the derivative of $G2_{\mathrm{dc}}$ [see Fig. 1(g)] to trigger dishabituation. To avoid false triggers, the threshold $T_{\mathrm{dishab-dc}}$ is applied only if the connection is near full habituation $(w \leq 1.8)$. The derivative of $G2_{\mathrm{ac}}(G2_{\mathrm{dc}})$ is computed by subtracting from the signal its average activity on the previous 50 ms (200 ms).

[1]The implementation of Kozma and Freeman [9] is equivalent to a slower time constant $\tau = 2s$. It must be noted, however, that the value of τ is not a matter of free choice, as it has an effect on the dynamics of the KIII model, and must be carefully selected.

[2]For values of $B \leq 1.5$, the ac response to a stimulus is similar to the basal state, as shown in Fig. 1(e) for $t = 1200$–1400 ms.

[3]The adaptive mitral-to-mitral connections are obtained through the (Hebbian) input correlation rule $W_{M1} = \sum_{\forall i} f(p_i p_i^T)$, where p_i is the input pattern for the ith odor proposed in Section III, and $f(\cdot)$ is a threshold function so that the elements in W_{M1} are either LOW or HIGH (diagonal elements are set to zero).

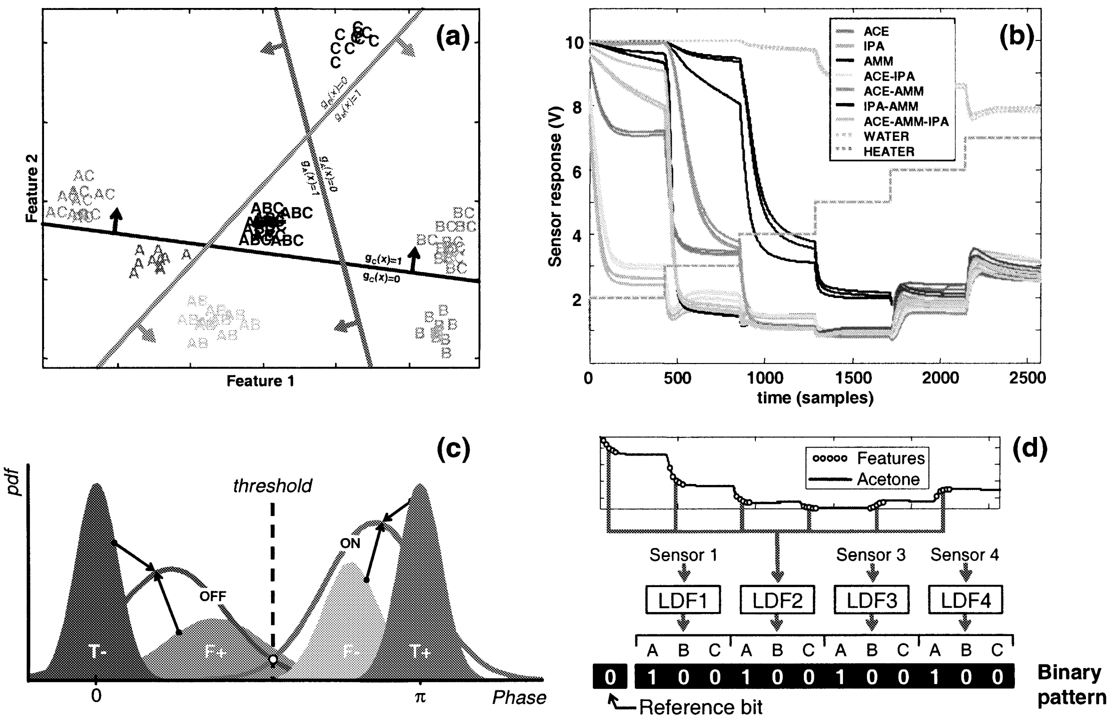

Fig. 2. (a) Illustration of odor-selective hyperplanes. (b) Response of a MOS sensor to odor mixtures. (c) Classification of G2 phases. (d) Feature extraction and binary code from staircase temperature transients.

III. Odor-Selective Hyperplanes

Inputs to the system are generated from the response patterns of a chemical sensor array. Although the KIII model can be stimulated directly with raw sensor data, this paper employs a preprocessing stage that yields a more suitable orthogonal binary representation [12]. The solution consists of partitioning sensor feature space into odor-selective regions, as depicted in Fig. 2(a) for a 2-D 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 that contain the odor. Therefore, each of these LDFs can be thought of as a very selective pseudosensor capable of detecting the presence of a particular odor that may be embedded in a complex background.

The rationale behind the use of LDFs on the front-end of the KIII model is twofold. First, it can be argued that the KIII inputs are more representative of glomeruli (GL) than of individual olfactory receptor neurons (ORNs). ORNs display a high level of convergence onto GL, a feature not captured by the KIII since it is a model of population dynamics. In addition, each GL preferentially receives projections from ORNs expressing the same receptor type, thus serving as a molecular feature extractor [13]. As a result of this chemotopic projection, different odors induce unique activation patterns across the GL layer, providing the means for separating odor quality from odor intensity, which cannot be accomplished at the ORN level. Thus, from a biological plausibility standpoint, the LDFs provide a labeled-line olfactory code. Second, LDFs are needed because ORNs and odor sensors have radically different coding mechanisms. More importantly, odor sensors have much broader cross-selectivities than ORNs, which causes collinearity problems and results in highly overlapped input patterns.

A. Chemical Sensor Array

A sensor array with four metal oxide semiconductors (MOS) [14] is employed to collect experimental data. MOS sensors are chemoresistors: exposure to an odor changes the resistance of the device, which is then measured with a voltage divider. The selectivity of a MOS sensor is a function of its operating temperature (around 400 $^{\circ}\mathrm{C}$), which is controlled by applying a voltage across a built-in heater. Thus, selectivity can be improved by capturing the sensor response at multiple heater voltages, a principle known as temperature modulation [12]. Based on this principle, a staircase heater voltage with six step inputs ranging from 2 to 7 V is used to excite the array, resulting in the response patterns shown in Fig. 2(b). The most informative part of the sensor transients correspond to the faster exponential decays [12]. In order to capture this information, five points spaced 2 s apart are extracted from the initial part of each transient. Features from the six transients are merged to form a 30-D feature vector per sensor, which is then processed with the LDFs to produce a 3-bit code per sensor, or a 12-bit code for the complete sensor array, as illustrated in Fig. 2(d). Processing each sensor independently allows the system to be robust against sensor failure by exploiting the pattern-completion capabilities of the KIII. A thirteenth bit, always set to zero, is also added to provide a reference phase.

IV. Results

To validate the proposed system, the sensor array was exposed to mixtures of Acetone (A), Isopropyl Alcohol (B), Ammonia (C), and water (neutral odor). Experimental data from each of the mixtures (A, B, C, AB, AC, BC, ABC, and N) was collected on three separate days, for a total of 24 samples. The system was evaluated using threefold cross-validation. For a given fold, data from two days was used to derive LDFs and hebbian connections, and data from the third separate day was used as a test set. To classify KIII activation patterns, G2 oscillations are interpreted as ON or OFF based on their phase relative to the reference channel. This phase code has been shown to be more robust than the amplitude of the channels [15]. A decision threshold for the phases is obtained as a Maximum A Posteriori (MAP) solution, as illustrated in Fig. 2(c). True negatives $(T-)$ are channels correctly classified as OFF by the LDFs, whose G2 outputs will then oscillate in

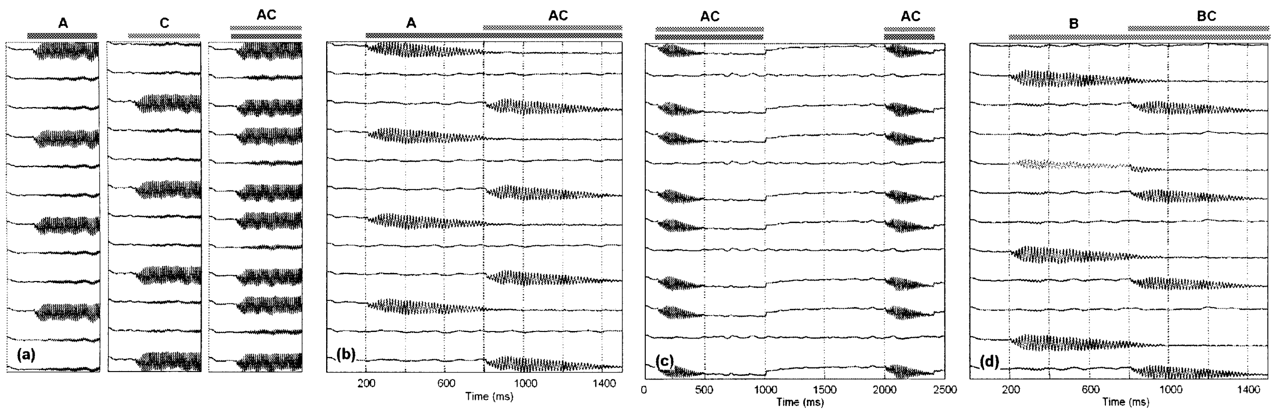

Fig. 3. (a) G2 output patterns of the KIII without habituation. (b) Mixture perception following habituation. (c) Reversibility of the habituation process. (d) Pattern recovery. (Reference bit not shown).

phase with the reference bit. False positives $(F+)$, on the other hand, are channels incorrectly classified as ON by the LDFs. Similarly, true positives $(T+)$ are channels correctly classified as ON, and false negatives $(F-)$ are those incorrectly classified as OFF. Thus, $F+$ and $F-$ represent errors introduced by the LDFs. Fortunately, the G2 channels in the case of $F+/F-$ oscillate in close phase with the correct outputs as a result of the hebbian connections. To derive a MAP threshold, $T-/F+$ cases are assumed to belong to one Gaussian density, and $T+/F$- cases to the other. When applied to the experimental data, the LDFs introduce errors in 18 of the 288 coding bits in the dataset (12 bits /sample $\times$ 24 samples), or an error rate of 6.25%. Segmentation of their corresponding G2 oscillations according to phase reduces the number of error bits down to 2, or a 0.69% error rate.

The habituation performance is analyzed on three separate scenarios. First, to illustrate the additivity of patterns, Fig. 3(a) shows the KIII response when exposed separately to samples of A, C, and AC. The habituation process is disabled to emphasize the steady-state response. The first experiment is designed to illustrate a shift in the perception of an odor mixture when the system has previously habituated to one of the components. The system is presented with odor A and allowed to habituate. At this time, binary mixture AC is presented. As shown in Fig. 3(b), the response to AC is as if only C was present, reproducing a known olfactory perception phenomenon [7]. The second experiment shows the ability of the KIII to fully recover from habituation to an odor. The model is excited with odor mixture AC and allowed to habituate. The sample is then removed and the KIII is allowed to dishabituate. When the sample is reintroduced, the KIII does not show any memory effects, as shown in Fig. 3(c). The final experiment further illustrates the pattern-completion capabilities of the system. When processing a test example for odor B (from day 3), the LDFs introduce an error on the fifth bit as a result of a distorted sensor transient. However, the system is able to induce an oscillation in the missing channel that is strong enough to trigger habituation. When subsequently exposed to a complete pattern of mixture BC, the KIII behaves as if it had been previously exposed to the complete pattern for odor B.

V. Conclusion

This paper has shown that the habituation and dishabituation processes in the KIII model can be triggered from changes in local ac and dc activity at each channel. When combined with a labeled-line input code, the system can simulate the effects of habituation in the processing of odor mixtures. The use of separate feature spaces for individual sensors exploits the associative-memory function of the KIII, allowing it to compensate for the majority of the errors at the inputs. The system has been validated on an array of temperature modulated metal-oxide sensors, but is not tied to a particular sensor system. The work presented in this paper has focused exclusively on odor quality. The effects of habituation on odor thresholds, and an extended representation to encode odor intensity, constitute future research directions.

References

[1] J. W. Gardner and P. N. Bartlett, *Electronic Noses Principles and Applications*. Oxford, U.K.: Oxford Univ. Press, 1999.

[2] D. Wang, J. Buhmann, and C. von der Malsburg, "Pattern segmentation in associative memory," *Neural Computat.*, vol. 2, pp. 94–106, 1990.

[3] O. Hendin, D. Horn, and J. J. Hopfield, "Decomposition of a mixture of signals in a model of the olfactory bulb," *PNAS*, vol. 91, no. 13, pp. 5942–5946, 1994.

[4] Z. Li and J. Hertz, "Odor recognition and segmentation by a model olfactory bulb and cortex," *Network: Computation in Neural Systems*, vol. 11, pp. 83–102, 2000.

[5] R. Gutierrez-Osuna and N. U. Powar, "Odor mixtures and chemosensory adaptation in gas sensor arrays," *Int. J. Artific. Intell. Tools*, vol. 12, no. 1, pp. 1–16, 2003.

[6] G. M. Shepherd, "Principles of specificity and redundancy underlying the organization of the olfactory system," *Microscopy Res. Tech.*, vol. 24, pp. 106–112, 1993.

[7] R. A. de Wijk, "Temporal Factors in Human Olfactory Perception," Doctoral, University of Utrecht, The Netherlands, 1989.

[8] D. Wang, "Habituation," in *The Handbook of Brain Theory and Neural Networks*, M. A. Arbib, Ed. Cambridge, MA: MIT Press, 1998, pp. 441–444.

[9] R. Kozma and W. J. Freeman, "Chaotic resonance—methods and applications for robust classification of noisy and variable patterns," *Int. J. Bifurc. Chaos*, vol. 11, no. 6, pp. 1607–1629, 2001.

[10] H. J. Chang, W. J. Freeman, and B. C. Burke, "Biologically modeled noise stabilizing neurodynamics for pattern recognition," *Int. J. Bifurc. Chaos*, vol. 8, no. 2, pp. 321–345, 1998.

[11] H. J. Chang, W. C. Freeman, and B. C. Burke, "Local homeostasis stabilizes a model of the olfactory system globally in respect to perturbations," *Int. J. Bifurc. Chaos*, vol. 8, no. 11, pp. 2107–2123, 1998.

[12] R. Gutierrez-Osuna, A. Gutierrez-Galvez, and N. Powar, "Transient response analysis for temperature modulated chemoresistors," *Sensors and Actuators B: Chemical*, vol. 93, no. 1–3, pp. 57–66, 2003.

[13] K. R. Sullivan, S. L. Sullivan, and L. B. Buck, "Information coding in the olfactory system: Evidence for a stereotyped and highly organized epitope map," *Cell*, vol. 79, pp. 1245–1255, 1994.

[14] *Figaro*. Osaka, Japan: Figaro Engineering, 1996.

[15] A. Gutierrez-Galvez and R. Gutierrez-Osuna, "Pattern completion through phase coding in population neurodynamics," *Neural Networks*, vol. 16, pp. 649–656, 2003.