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Report Title

Final Report: Multimodal Olfactory Scene Analysis

ABSTRACT

This describes our effort for understanding biological and artifical olfactory systems
along three multi-disciplinary fronts:
1. Experimental characterization of biological olfactory systems in their speed and adaptiveness
to novel odors
2. Mathematical modeling of the effective of various olfactory search strategies
3. Machine learning algorithms for analyzing olfactory sensor data

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List of papers submitted or published that acknowledge ARO support during this reporting period. List the papers, including journal references, in the following categories:

(a) Papers published in peer-reviewed journals (N/A for none)

Ermentrout, B., Wang, J. W., Flores, J., Gelperin, A. (2004) Model for transition from waves to synchrony in the olfactory lobe of Limax. J Comput. Neurosci., 17:365-383.

Dalton. P., Gelperin, A., Preti, G. (2004) Volatile metabolic monitoring of glycemic status in diabetes using electronic olfaction. Diabetes Technol. Therapeutics 6: 534-544.

Staii, C., Johnson, A.T., Chen, M., Gelperin, A. (2005) DNA-decorated carbon nanotubes for chemical and biological sensing. Nano Letters, 5: 1774-1778.

Gelperin, A. (2006) Olfactory computations and network oscillations. J. Neurosci., 26:1663-1668.

Gelperin, A., Hildebrand, J., Eisner, T. (2006) Vincent Gaston Dethier In: Biographical Memoirs, National Academy of Sciences. In press.

Goel, P. and Gelperin, A. (2006) A neuronal network for the logic of Limax learning. J Comput Neurosci. In press

Rinberg, D., Koulakov, A., Gelperin, A. (2006) Sparse odor coding in the behaving mouse. J. Neurosci. In press.

Rinberg, D., Gelperin, A. (2006) Olfactory neuronal dynamics in behaving animals. Seminars in Cell and Developmental Biology. In press.

Y. Lin and D.D. Lee (2004) Bayesian regularization and nonnegative deconvolution for time delay estimation. Advances in Neural and Information Processing Systems.

N.G. Hockstein, E.R. Thaler, Y. Lin, D.D. Lee, C.W. Hanson (2005) Correlation of pneumonia score with electronic nose signature: a prospective study. Annals of Otology, Rhinology, and Laryngology 111, 7.

Y. Lin and D.D. Lee (2006) Bayesian regularization and nonnegative deconvolution (BRAND) for room impulse response estimation. IEEE Trans. Signal Processing 54, 839-847.

Y. Lin and D.D. Lee (2006) Bayesian L1-norm sparse learning, to appear in International Conference on Acoustics, Speech, and Signal Processing, V-605-608.

Number of Papers published in peer-reviewed journals: 12.00

(b) Papers published in non-peer-reviewed journals or in conference proceedings (N/A for none)

“Statistical signal processing with nonnegativity constraints,” L. K. Saul, F. Sha, and D. D. Lee, Proceedings of the Eighth European Conference on Speech Communications 2, 1001-1004 (2003).

“Nonnegative deconvolution for time of arrival estimation,” Y. Lin, D. D. Lee and L. K. Saul, International Conference on Acoustics, Speech, and Signal Processing (2004).

“Bayesian regularization and nonnegative deconvolution (BRAND) for acoustic echo cancellation,” Y. Lin and D. D. Lee, to appear in IEEE Workshop on Applications of Signal Processing to Audio and Acoustics (2005).

Number of Papers published in non peer-reviewed journals: 3.00

(c) Papers presented at meetings, but not published in conference proceedings (N/A for none)

"Machine learning and robotics," Workshop on Scattering Methods for Structure and Dynamics of Soft Condensed Matter, Florence, Italy, October 2005.

"Sensorimotor learning in robotics," Robotics Institute, Carnegie Mellon University, Pittsburgh, PA, March 2005.

"Sensorimotor learning in robotics," Broad Area Colloquium for AI, Geometry, Graphics, Robotics, and Computer Vision, Stanford University, Stanford, CA, March 2005.

"Machine learning for sensorimotor processing," Kavli Institute for Theoretical Physics, UCSB, Santa Barbara, CA, September 2004.

Number of Papers not Published: 4.00

(d) Manuscripts

Infotaxis: searching without gradients, M. Vergassola, E. Villermaux, B. I. Shraiman, submitted to Nature.

Number of Manuscripts: 1.00

Number of Inventions:

Graduate Students

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Final Report: Multimodal Olfactory Scene Analysis

Alan Gelperin, Boris I. Shraiman, Daniel D. Lee

July 25, 2006

Project Description

This project was concerned with basic scientific problems in understanding biological olfactory systems and developing artificial olfactory devices. The scientific thrusts of this project were developed along three complementary directions. We studied the biological basis of odor decision making in neurophysiological experiments. We also mathematically modeled how olfactory signals may be effectively located during search. Finally, we also developed machine learning algorithms to effectively deal with high-dimensional olfactory sensor signals.

Project Results

Speed-accuracy tradeoff in olfaction

The basic psychophysical principle of speed accuracy tradeoff (SAT) has been used to understand key aspects of neuronal information processing in vision and audition, but has not yet been demonstrated in olfaction. In designing an autonomous robot with an onboard olfactory guidance system, we need to optimize the tradeoff between length of odor sampling and speed of decision-making about the chemical nature of the odorant being sampled. We investigated this issue in a biological olfactory system to develop insights for subsequent use in the robotic system. We found, for the first time, direct evidence for the operation of SAT in olfaction.

To obtain evidence for SAT in olfaction we developed a behavioral testing paradigm for mice in which both the duration of odor sampling by the mouse and the difficulty of the odor discrimination task were controlled by the experimenter. We found that the accuracy of odor discrimination increases with the duration of imposed odor sampling and that the rate of this increase is slower for harder odor discrimination tasks. We also developed a unifying explanation of two previous, seemingly disparate, experimental results in the literature on 1) the dependence of odor discrimination accuracy on the difficulty of an odor discrimination task with an approximately constant odor sampling time, and 2) the dependence of odor sampling timing on difficulty of odor discrimination with approximately equal accuracy. The presence of SAT in olfaction provides strong evidence for temporal integration in olfaction and puts a constraint on models of olfactory processing.

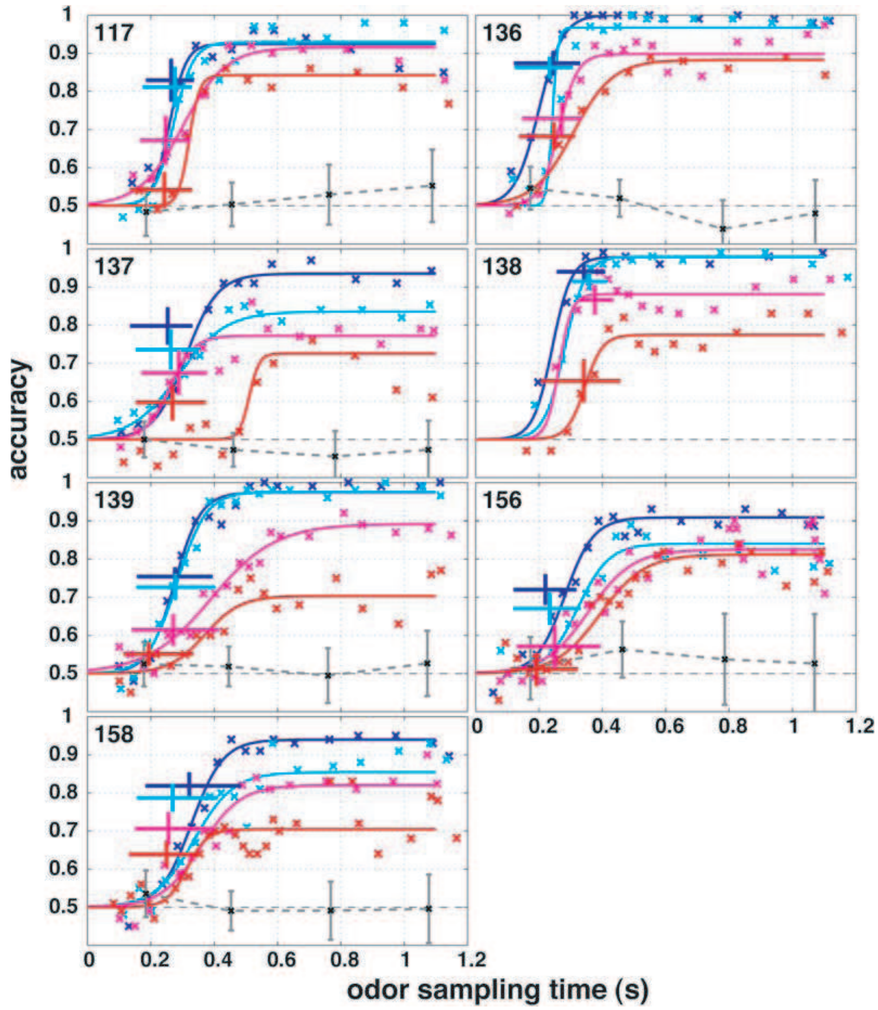

Figure 1: Odor recognition accurary as a function of exposure time and task difficulty in individual mice.

The mouse olfactory system can make very difficult odor discriminations in 1 3 active odor samples (sniffs), occurring over 140 430 msec at a sniff frequency of 7 Hz. To make a series of odor discrimination tasks of graded difficulty, we mixed two pure odors in varying proportions and asked the mouse to identify the dominant component of the mixture. The hardest odor discrimination task is to identify the dominant component in a mixture of 54% odor A and 46% odor B. Mice clearly required longer odor sampling times to maintain accuracy on this difficult task. In designing artificial odor sensors and pattern recognition algorithms, we will aim to duplicate this feat of accurate identification of the dominant odor in a binary mixture with subsecond sampling and analysis time.

Sparse odor coding in the mammalian olfactory bulb

Important clues about optimum odor pattern recognition will be derived from a better understanding of how patterns of sensory neuron firing are transformed by synaptic processing into patterns able to be stored as odor memories with minimal overlap and confusion of a series of stored patterns. To obtain more complete understanding of stimulus representations optimized for pattern discrimination and memory storage, we studied the responses of mitral cells in the mouse olfactory bulb while the mouse performed odor-guided memory retrieval tasks. Odor-elicited mitral cell activity represents the results of the first stage of odor processing in the olfactory bulb. Most of our knowledge about mitral cell activity has been obtained from recordings in anesthetized animals. We compared odor-elicited changes in the firing rate of mitral cells in awake behaving mice and in anesthetized mice. We found that odor-elicited changes in mitral cell firing rate were larger and more frequently observed in the anesthetized than in the awake condition. Only 27% of mitral cells that showed a response to odors in the anesthetized state, were also odor responsive in the awake state. The amplitude of the mitral cell response in the awake state was smaller and some of the responses changed sign compared to the responses of the same mitral cell in the anesthetized state. We are able to follow the activity of single mitral cells from the awake state to the anesthetized state and back again to the awake state using new electrode implant technology incorporating movable single unit electrodes driven by micromotors in the electrode implant chamber. Our results using this new technology show that the odor representation in the olfactory bulb is much sparser in the awake behaving mouse than in anesthetized preparations. We also developed a model of odor representation to provide a qualitative explanation of a mechanism that may be responsible for the sparsening of odor representation in the awake animal compared to the anesthetized animal. The model we proposed makes testable predictions about the nature and effects of intrinsic and extrinsic modulation of synaptic interactions in the olfactory bulb.

Infotaxis: searching for odors without gradients

Chemotactic search strategies based on local concentration gradients require concentration to be sufficiently high so that its average difference measured at two nearby locations is larger than typical fluctuations. The signal-to-noise ratio depends of course on the averaging time and might be improved by waiting. However, average concentration may be decaying rapidly, e.g. exponentially, with the distance away from the source and in this weak signal-to-noise (dilute) case waiting becomes worse than exploratory motion. An example of organisms performing olfactory search in a dilute limit is provided by moths which use pheromones to locate their mates. Moths are known to proceed upwind via counterturning patterns of extended (“casting”) or limited (“zigzagging”) crosswind width thought to correlate with low and high rates of odor detection. A practical situation involving the challenge of searching in dilute conditions is encountered in the design of sniffers - robots that track chemicals emitted by drugs, chemical leaks, explosives and mines. Existing methods apply to high-concentration conditions, where chemotactic or plume-tracking strategies might be employed.

To balance the competing demands of exploration and exploitation in olfactory search, we propose the following “infotaxis” strategy. At each time step, the searcher chooses the direction

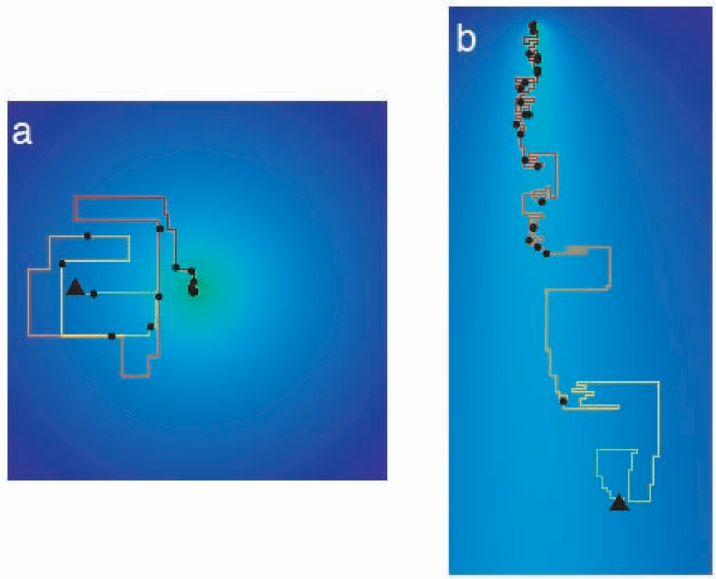

Figure 2: Olfactory search patterns guided by information theory criterion without (a) and in the presence (b) of wind.

which locally maximizes the expected rate of information acquisition. Specifically, the searcher chooses, among the neighboring sites on a lattice and standing still, the move which maximizes the expected reduction in entropy of the posterior probability field. The intuitive idea is that entropy decreases (and thus information accumulates) faster close to the source because cues arrive at a higher rate, hence tracking maximum rate of information acquisition will guide to the source much like concentration gradients in chemotaxis.

Sparse Bayesian learning for odor classification

To effectively learn odor features from a small amount of training data, we have investigated a Bayesian framework for learning the optimal regularization parameters in the L_1-norm penalized least-mean-square (LMS) problem, which is also known as LASSO or basis pursuit. Although the setting of the regularization parameters is critical for deriving a correct solution, most existing methods determine them in a empirical manner. By contrast, our approach infers the optimal regularization setting under a Bayesian framework, which enables an independent regularization scheme where each coefficient (or weight) is associated with an independent regularization parameter. Simulations are employed to illustrate the dramatic improvement by the new proposal in discovering sparse structure from noisy data.

We consider the problem of finding a sparse solution of a least-mean-square (LMS) function. This problem is a key to many applications in signal processing and L_1-norm regularization has

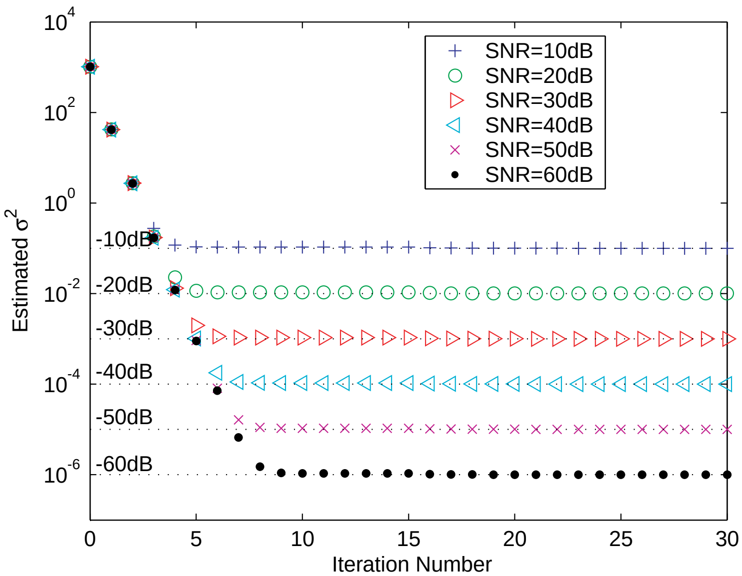

Figure 3: Convergence of the noise estimation in Bayesian L_1-norm sparse learning with varying amount of added noise. The input signal was normalized so that it had unit power.

been well recognized as an effective approach for deriving the sparse LMS solution:

$$\mathbf{w}^* = \arg\min_{\mathbf{w}} \frac{1}{2}\|\mathbf{y} - \mathbf{\Phi}\mathbf{w}\|^2 + \hat{\lambda}\sum_{i=1}^{M}|w_i|, \tag{1}$$

where $\mathbf{y}$ is an $N \times 1$ data vector, $\mathbf{\Phi}$ is an $N \times M$ designed matrix, $\mathbf{w}^*$ is the $M \times 1$ weight vector that need to be optimized, and $\hat{\lambda}$ is the regularization parameter that balances the favoring between the LMS fitting and the solution sparseness described by the L_1-norm. We show how these parameters may be automatically learned from a small amount of training data.

Summary

This project has resulted in a number of scientific findings as well as provided the basis for the further development of artificial olfactory search and recognition systems:

- Characterization of the accuracy of biological odor discrimination.
- Evidence of sparse coding in the olfactory cortical areas.
- Elucidation of the advantages of certain olfactory search strategies.
- Development of sparse Bayesian learning algorithms for odor recognition.