Optimal encoding of odor concentration for olfactory navigation is approximated by the Hill nonlinearity. One-dimensional sampling grids (triangles) within a dynamic odor plume. Since the odor concentration varies with time, each location yields a distribution of odor concentrations. The large histogram shows the distribution of odor concentrations across all grid points; the two smaller histograms show the distribution of odor concentrations at two example grid points.

C-E. Evaluation of schemes encoding odor concentration. C: Locations across the grid points are assigned a priori probability. D: An odor sampler is obtained at a randomly-chosen grid point, and encoded into a code word that represents a discrete range of odor concentrations. Several alternatives discretizations are considered. E: For each code word, the a posteriori probability of location within the grid is computed via Bayes Theorem. For each discretization, we then compute the Shannon mutual information between location and code word. Modified from (Boie, Cor EOF et al., 2018).

Experimental Methods

Spatiotemporal Measurement of Odor Concentrations in a Turbulent Air Plume

An odor surrogate (acetone made neutrally buoyant by mixing with air and helium) was isotropically released into a wind tunnel at the center of its entrance. Turbulence was introduced by an upstream grid (6.4 mm diameter rods and a 25.5 mm mesh spacing, followed by a 1.5 m long honeycomb section). Fluorescence was induced with a 4 mm thick light sheet from a Nd:YAG 255 mJ pulsed laser. Fluorescence, proportional to acetone concentration, was imaged using a high efficiency cMOS camera. Modified from Cor EOF et al., 2018.

Sampling Grids. Three two-dimensional grids (below), superimposed on contour lines corresponding to average odor concentrations of 0.1, 0.03, and 0.01 times the inlet concentration. One dimensional sampling grids (right) in X and Y directions. Analysis at these grids yielded similar results (not shown).

A: Odor concentration is measured at multiple grid locations (triangles) within a dynamic odor plume. B: Since the odor concentration varies with time, each location yields a distribution of odor concentrations. The large histogram shows the distribution of odor concentrations across all grid points; the two smaller histograms show the distribution of odor concentrations at two example grid points.

Olfactory navigation is a sensorimotor behavior that is critical to the survival of a wide range of organisms. It is made computationally challenging by the turbulent nature of natural olfactory plumes. Evolutionarily successful organisms accomplish olfactory navigation by making navigation decisions on a moment-by-moment basis. These decisions are necessarily based on a limited knowledge of the odor plume. Limitations arise not only because measurements are restricted to sensor’s locations, but also because the sensors have limited accuracy and bandwidth. Our focus here is how these limited resources are best used. We take an information-theoretic approach in which we first how odor concentration can be encoded into a fixed number of bits in a way that maximizes information about location within a plume.

Introduction

Overview

Results

Algorithm

Dynamic programming strategy for determining the discretization of a range into M code words that maximizes the Shannon information about an underlying variable (location).

The key observation is that in an optimal discretization of an interval, any sub-interval is optimally discretized. This holds because of the chain rule for entropy. The optimal discretization of the entire interval can then be built from a library of optimal discretizations of sub-intervals. Initially, a library of optimal discretizations of [0 1] into 2 segments is created (Blue and red symbols). Iteratively, each library is used to build a library of optimal discretizations containing one additional segment.

The optimal segmentation for the 10 cm/sec unbounded environment, full grid, A: Positions of the cutpoints, for 2 to 32 code words. (M). For each value of M, there are M-1 cutpoints, which separate the concentration range into segments corresponding to the code words. B: Stepwise nonlinearities corresponding to selected values of M. As shown by the arrows for M=2 (black) and M=3 (blue), the nonlinearities in B have a step increment of height 1/M at the cutpoints in A. Histogram equalization corresponds to the diagonal. C: As in B, but plotted as a function of normalized concentration, rather than linear.

Summary & Conclusions

We used a combined experimental and theoretical approach to analyze optimal coding strategies for the purpose of olfactory navigation.

Planar laser-induced fluorescence was used to measure spatiotemporal characteristics of turbulent plumes in air.

A new dynamic programming algorithm was used to identify optimal coding schemes.

Histogram equalization, the optimal strategy for encoding information about concentration, is sub-optimal for transmitting information about location. For location, gender nonlinearities yield greater information per code word.

The advantage of a more gently saturating nonlinearity is even greater when compressibility of the code word stream is taken into account.

Optimal behavior is approximated by a Hill receptor binding isotherm, a model with binding constant c_0 at the mean odor concentration.

References


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