Information-theoretic analysis of active bi-antennal sensing for olfactory navigation

Jonathan D. Victor[1], Aaron C. True[2], John P. Crimaldi[2]

[1]Feil Family Brain and Mind Research Institute, Weill Cornell Medical College, New York, NY USA;

[2]Civil, Environmental & Architectural Engineering, University of Colorado, Boulder, CO USA

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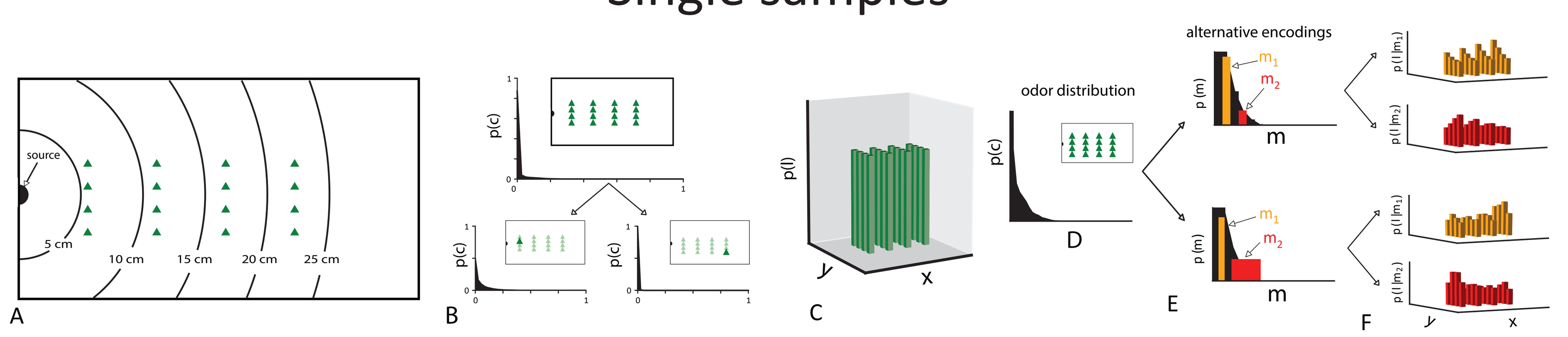
Introduction

To meet the challenge of olfactory navigation, organisms typically use pairs of sensors and also active sensation (e.g., antennal motion or sniffing). Active sensation can modify the spatiotemporal characteristics of the olfactory environment even before it is sensed: it can influence the region of space that is sampled, it can produce a local mixing of odor concentrations within this region.

To explore the utility of these strategies, we combined an information-theoretic approach with measurements of the spatiotemporal characteristics of real plumes. The information-theoretic analysis determined the mutual information between odor concentrations at a pair of sensors, and relative location of the sensor pair to the plume source. We focused on how this mutual information varied with coding strategy, and how the optimal coding strategy depends on the olfactory environment.

Information-theoretic strategy

Single samples



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.

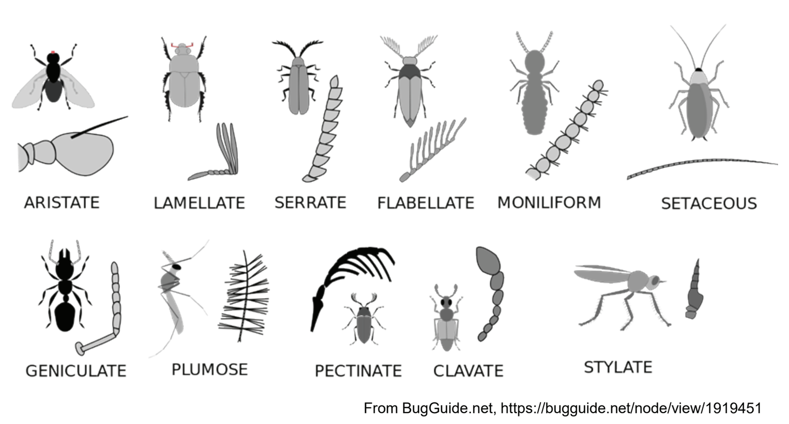
C-F: Evaluation of coding schemes. C: Grid locations have equal a priori probability. D-E: An odor sample obtained at a randomly-chosen grid point (D) is encoded into a word that represents a discrete range of odor concentrations (E). Several alternative discretizations are considered. F: For each code word, the a posteriori probability of location within the grid is computed via Bayes Theorem. For each discretization, we compute the Shannon mutual information between location and code word. Modified from Boie et al. 2018.

Paired samples

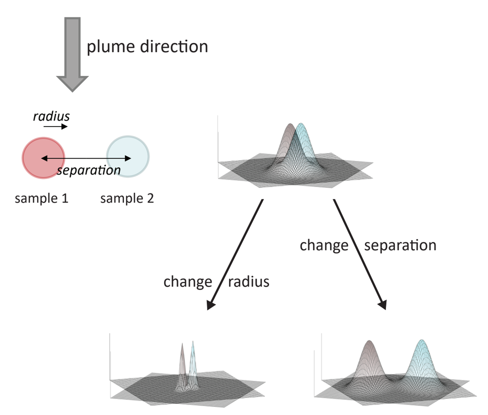
To extend this strategy to analysis of bi-antennal sampling, each location within the plume (A) is sampled by left and right sensors, oriented across the plume. The histogram of odor concentrations at each location (D) becomes a bivariate distribution, and discretizations of the odor concentration range into coding intervals (E) become discretizations of a two-dimensional distribution of odor concentrations into coding regions (see Results, upper left).

Computational Methods

Antennal shapes



Sampling model



Rather than attempt to model the details of how antennal movements interact with olfactory plumes, we considered an abstraction, in which individual odor samples represented a Gaussian-weighted average of a region of space. Size and separation of the Gaussian samples were varied parametrically. We also considered models in which the region sampled by each antenna did not cross the midline.

Mutual information was computed between samples of odor concentration and location, at 49 sites in a 7 x 7 grid within each plume.

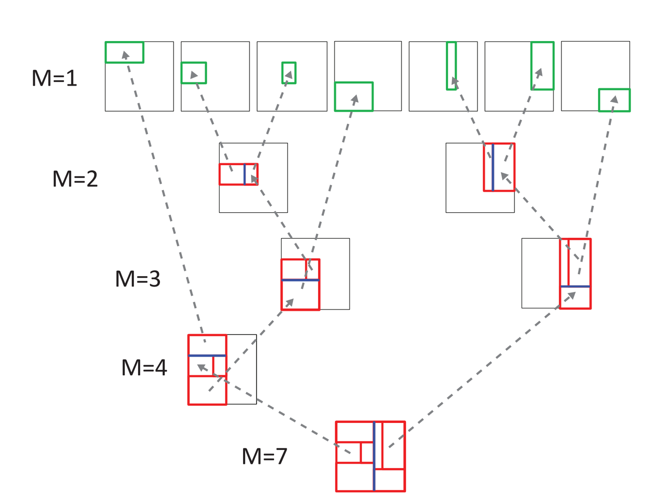
Active sampling was caricatured by local mixing at a pair of sensors.

- Sensor separation varied from 1.5 to 46 mm.
- Mixing volume was a Gaussian of radius 0.74 to 23 mm.
- We considered interpenetrating Gaussians (shown), and Gaussians that were truncated at the midline (not shown).

Information-theoretic details.

- We partitioned the space of paired odor concentration samples (cLeft,cRight) into a fixed number of code words (2, 4, …, 64).
- For each number of code words, we identified the partitioning (i.e., the coding scheme) that maximized the mutual information between the sample location and code words.

Partitioning the coding space via dynamic programming

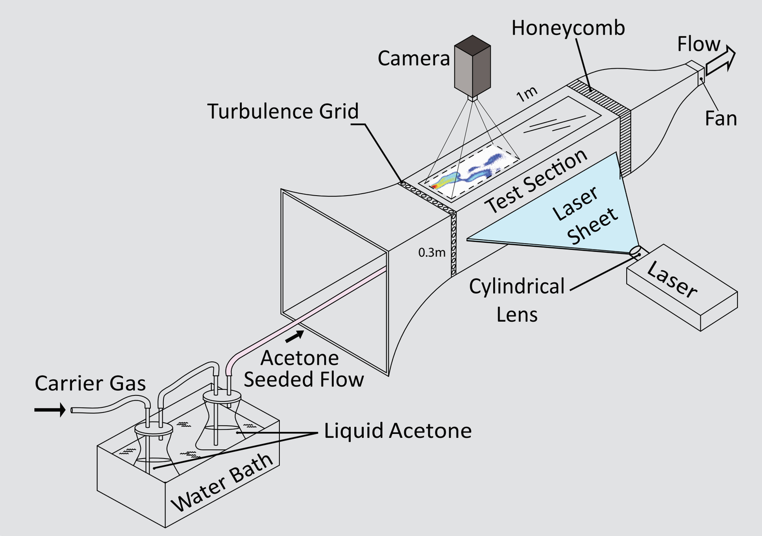


Optimizing the partitioning

To optimize the partitioning of coding space, we started with a dynamic programming algorithm, illustrated above. Briefly, mutual information was computed for all subdivisions of coding space into adjoining rectangles (first two rows), and this library was used to determine the optimal partitioning into larger numbers of rectangles. The optimal Mondrian-like partitioning was then refined by a Metropolis (1953) search algorithm applied to small shifts of the boundaries of coding regions.

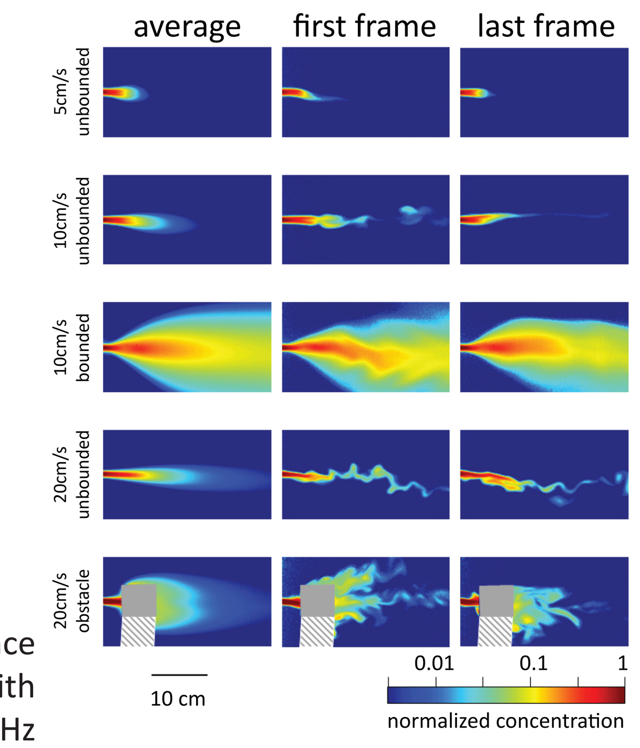
Experimental Methods

Spatiotemporal Measurement of Odor Concentrations in a Turbulent Air Plume



An odor surrogate (acetone made neutrally buoyant by mixing with air and helium) was isokinetically released into a wind tunnel at the center of its entrance. Turbulence was induced by an entrance grid (6.4 mm diameter rods and a 25.5 mm mesh spacing, followed by a 15 cm long honeycomb section). Fluorescence was induced with a 1 mm thick light sheet from a Nd:YAG 266nm pulsed laser. Fluorescence, proportional to acetone concentration, was imaged using a high-efficiency sCMOS camera. Modified from Connor et al., 2018.

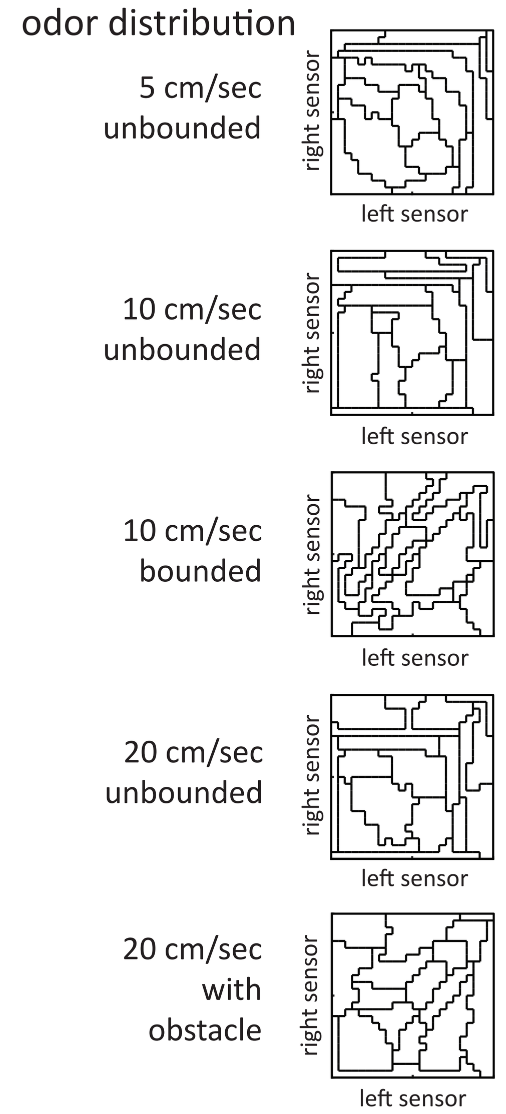
Spatiotemporal odor distributions were obtained via planar laser-induced fluorescence measurements of real plumes. We analyzed plumes with realistic advection speeds (5-20 cm/s), with and without a nearby boundary. •Spatial resolution: 0.74 mm pixels •Temporal resolution: 30 Hz • Region size: 216 x 406 pixels (160 x 300 mm).



Five Olfactory Environments Heat maps show average odor intensity (first column), and snapshots of odor intensity on the first and last frames of data collection (last two columns); note that the color scale is logarithmic and covers a concentration ranging from 1 (equal to the inlet concentration) down to 0.003. For the bounded dataset, a false-floor was placed just under the release point. For the obstacle dataset, the obstacle is indicated by the gray square in the plume centerline, and the region of the plume that could not be imaged because of this obstacle is indicated by the hatched parallelogram below the centerline.

Results - Coding strategies

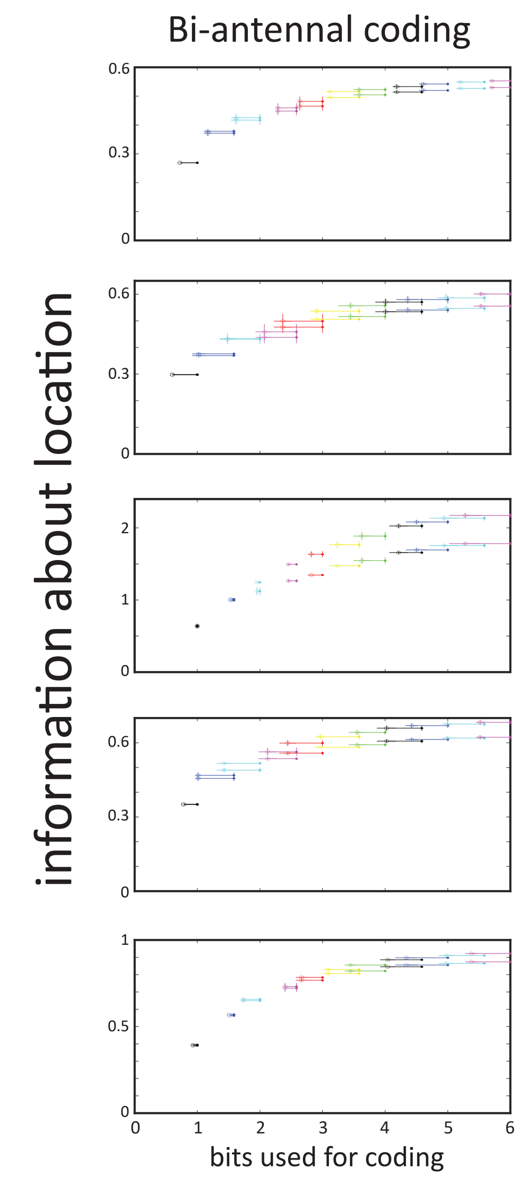
Optimal coding of bivariate odor distribution



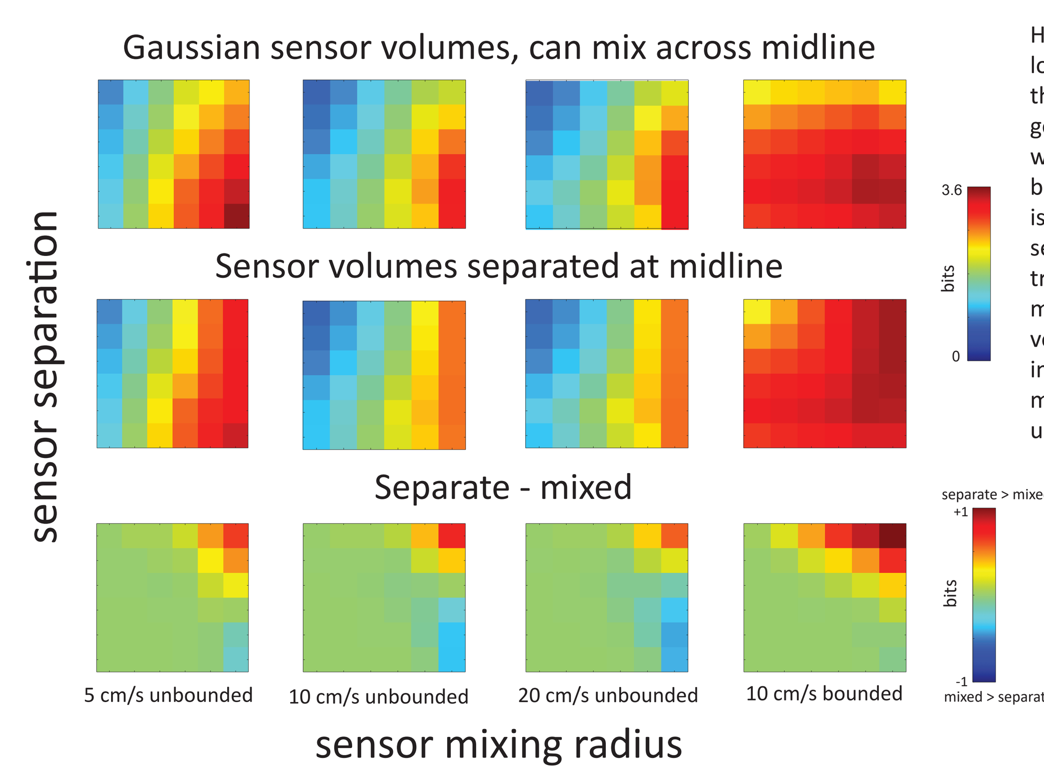
Left: Encoding paired samples of odor concentrations to maximize information about source location. For the bounded-flow (diffusive) environment, code word boundaries lie primarily along the diagonal, indicating that the side-to-side difference in odor concentration is informative. For the other environments, many code word boundaries delineate high odor concentrations, indicating that intermittent high-concentration transients are informative. Axes indicate odor concentration in quantiles.

Right: Analysis of bi-antennal coding as a function of the number of code words. Upper curve: information transmitted by the optimal partitioning of the paired odor samples into 2 to 64 code words (partitioning for 24 code words is shown on left). Lower curve: information transmitted if sensor identity (L vs R) is ignored. The large loss for the bounded-flow (diffusive) environment indicates that the sign of the left-minus-right difference is informative. Abscissa indicates the number of bits required to transmit the code words with (open circles) and without (closed circles) lossless compression.

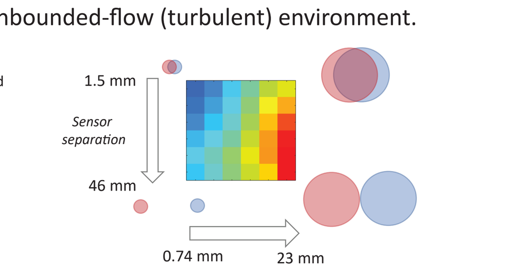
Bi-antennal coding



Results - Influence of active sensing via local mixing



Heatmaps show the information about source location transmitted by a pair of sensors that average the odor concentration via local mixing. Information generally increases with increasing mixing radius and with increasing sensor separation, but for the bounded-flow (diffusive) environment, information is lost for the largest mixing radii or sensor separations. The bottom row compares information transmitted for sensor volumes that mix across the midline, vs. those that remain separate. Separate volumes are favored for small sensor separations and in the bounded-flow (diffusive) environment, but mixing across the midline can be favorable in an unbounded-flow (turbulent) environment.



Summary and Conclusions

Combining bi-antennal sampling with active sensing has considerable advantages for odor navigation.

- Information about source location is maximized by joint encoding of a pair of odor concentrations.
  - For turbulent plumes, the optimal coding strategy signals the presence of a high concentration at either sensor, without regard to sensor identity.
  - For diffusive plumes, the optimal coding strategy signals the signed difference between the odor concentration at the two sensors.
- The benefit of two sensors increases with increasing sensor separation.
- Mixing the local environment prior to sampling increases the amount of information, and for turbulent plumes, mixing across the midline can be beneficial.

References

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