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

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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

Computational Methods

Antennal shapes

Sampling model

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.

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