Olfactory navigation: information theoretic scene analysis motivating a history-based algorithm

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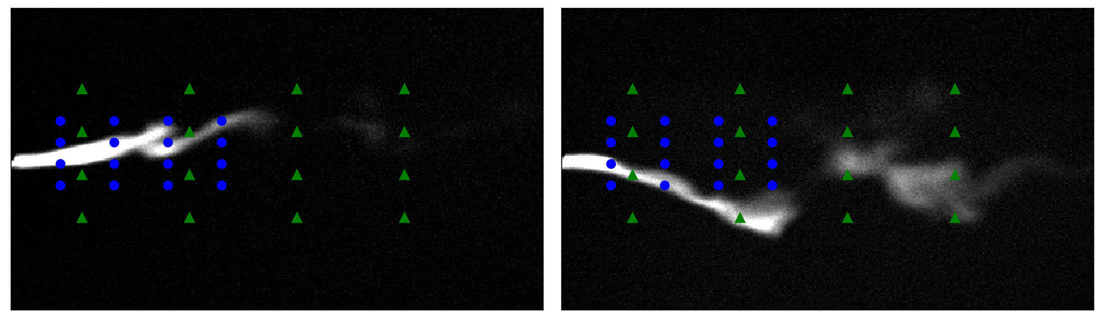
Introduction

Locating a food source or a mate based on olfactory cues is a challenging task since instantaneous concentration gradients do not, typically, point towards the source. Proposed navigation algorithms range from models with full spatial map to evaluating only local cues to guide behavior. A similar diversity is found in what features of the olfactory scene are measured (such as *instantaneous concentration, intermittency, time between odor encounters*).

Here we are interested in the intrinsic utility of these different kinds of features in determining the location of an odor source. We therefore used an information-theoretic approach to comparing different encoding strategies. We found that resolving concentration differences is less important than obtaining multiple samples, either in time or space. As we show via a simple navigational model, encoding only two levels of concentration can suffice to find the source of an odor when coupled with temporal sampling.

Environment

Odor molecules are volatile and often travel on turbulent plumes. To study a natural olfactory scene, we measured concentrations of a neutrally-buoyant odor surrogate by *planar laser-induced fluorescence*[1].



Two typical snapshots are shown above. We sampled eight minutes of concentration data at 15Hz (yielding 7200 samples at each of 495 × 281 pixels). In order to quantify how useful different cues are, we use the framework of information theory. We chose a narrow and a wide grid of 16 locations ($\mathcal{L}$; blue circles and green triangles above) to evaluate how much information is provided through different encoding strategies.

Method

Following Shannon[1], the mutual information is

$$I(\mathcal{L},\mathcal{M}) = H(\mathcal{L}) - \sum_{m\in\mathcal{M}} p(m) H(\mathcal{L}|m),$$

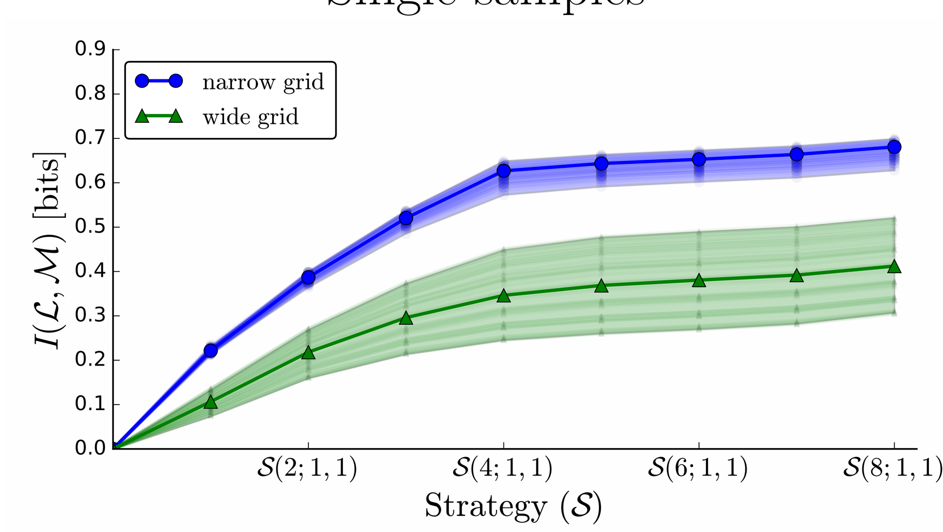
where $H(\mathcal{L})$ is the entropy of the probability distribution prior to taking sample m, and $H(\mathcal{L}|m)$ is the conditional entropy given m. The posterior distribution is obtained by Bayes theorem after measuring the code word m, which can comprise one or more spatial and temporal measurements. We compare different strategies ($\mathcal{S}$) of encoding odor measurements, using the notation

$$\mathcal{S}(n_{\text{bits}}; k_{\text{spatial}}, k_{\text{temporal}}),$$

where n_{bits} denotes the number of bits that resolve concentration, k_{spatial} is the number of spatial samples ($k_{\text{spatial}} \in \{1, 2\}$) and k_{temporal} is the number of consecutive samples in time ($k_{\text{temporal}} \in \{1, \ldots, 8\}$). Control analyses showed that our estimates of mutual information were not data-limited.

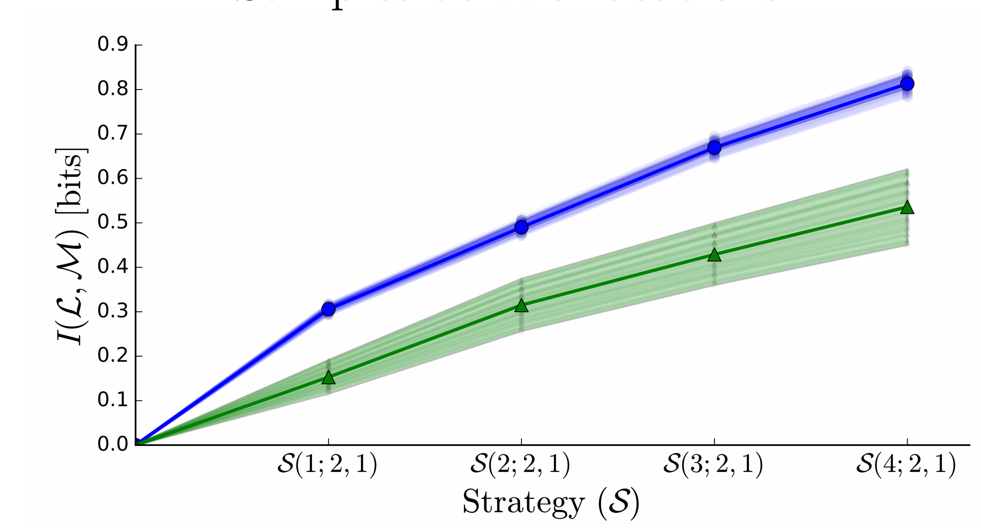
Comparison of different encoding strategies

Single samples



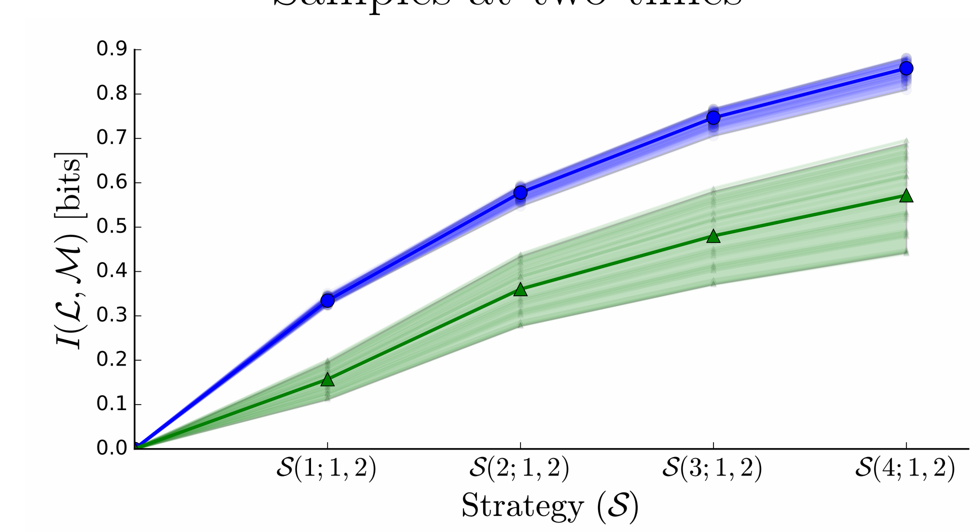
Information saturates with increasing concentration resolution.

Samples at two locations



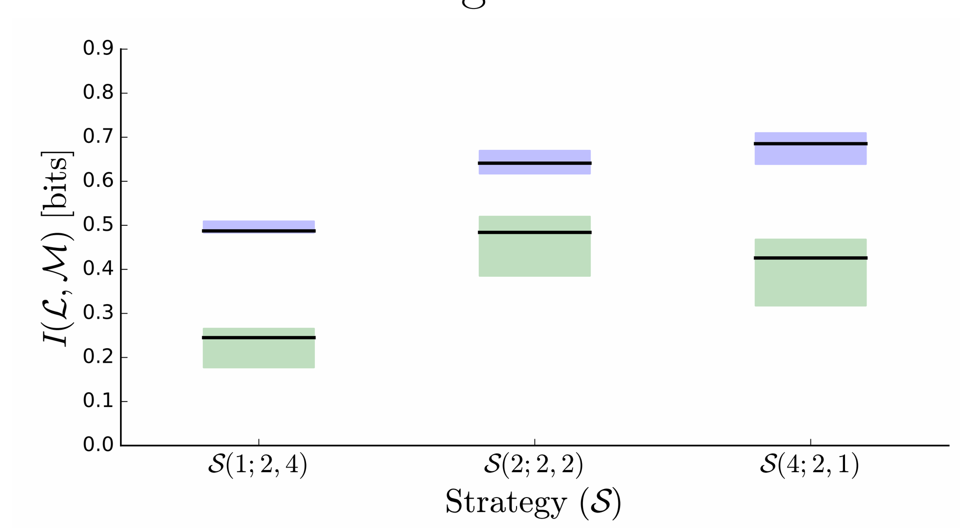
Sampling at two locations provides more information at lower concentration resolution.

Samples at two times

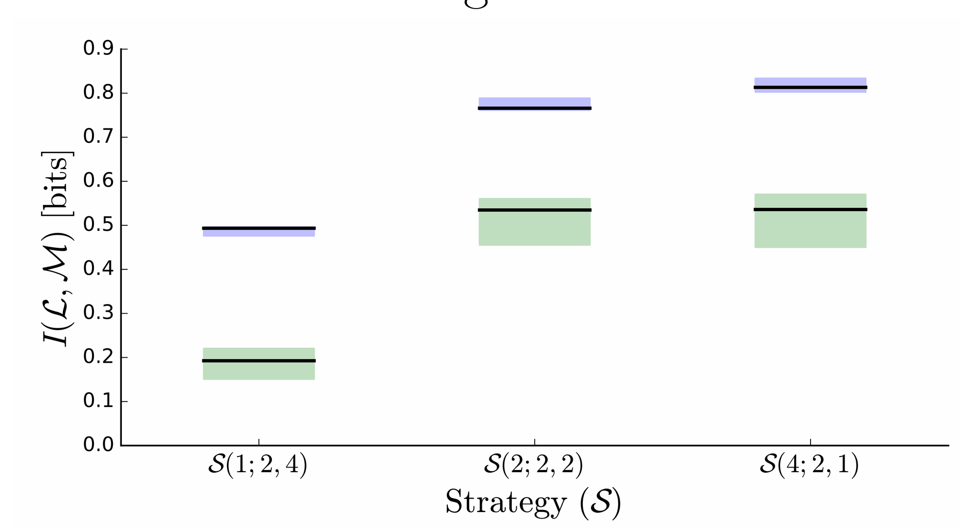


Sampling at two times also provides more information at lower concentration resolution.

Two sensors aligned cross-stream

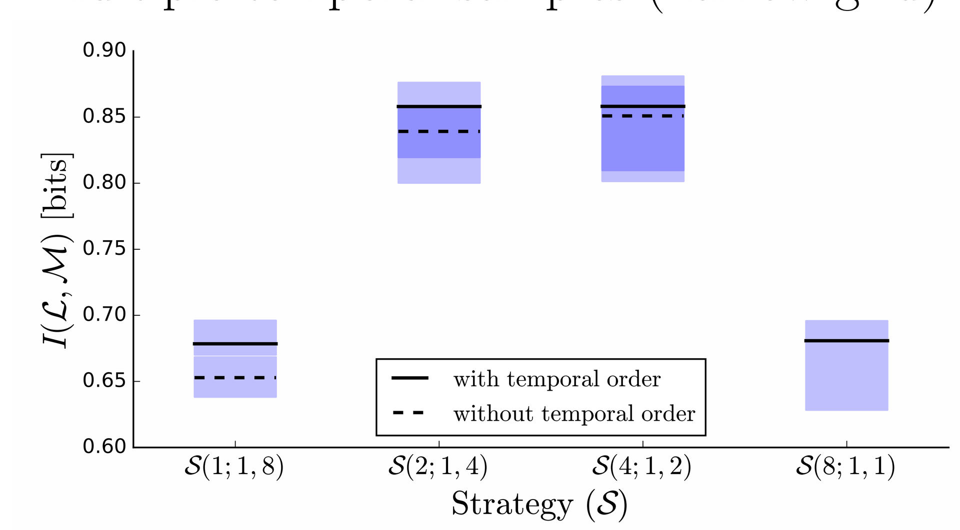


Two sensors aligned downstream

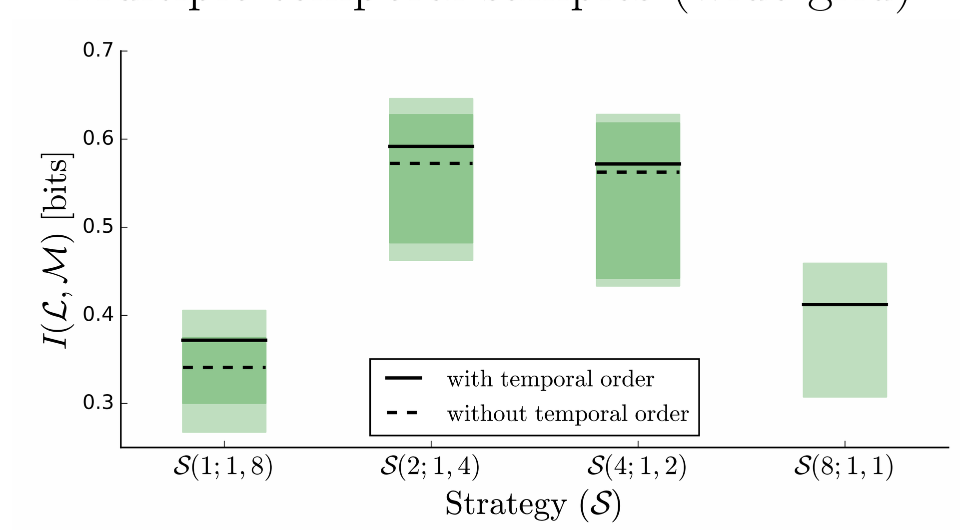


Allocating 8 bits to 2 or 4 spatiotemporal samples yields more information than allocating them to 8 samples.

Multiple temporal samples (narrow grid)



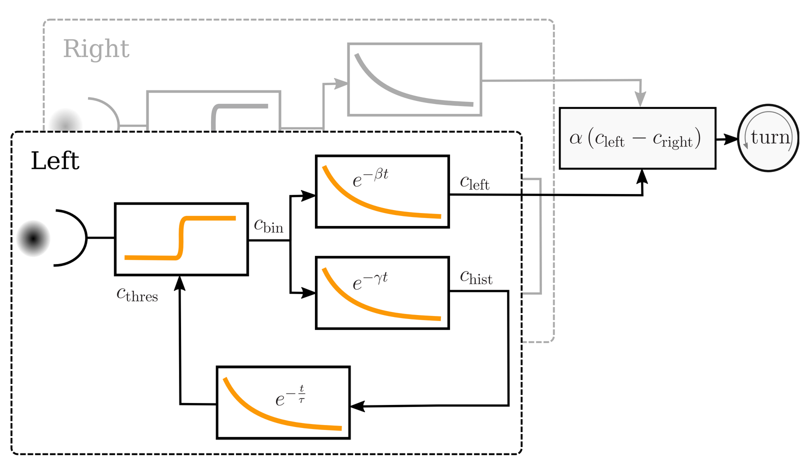
Multiple temporal samples (wide grid)

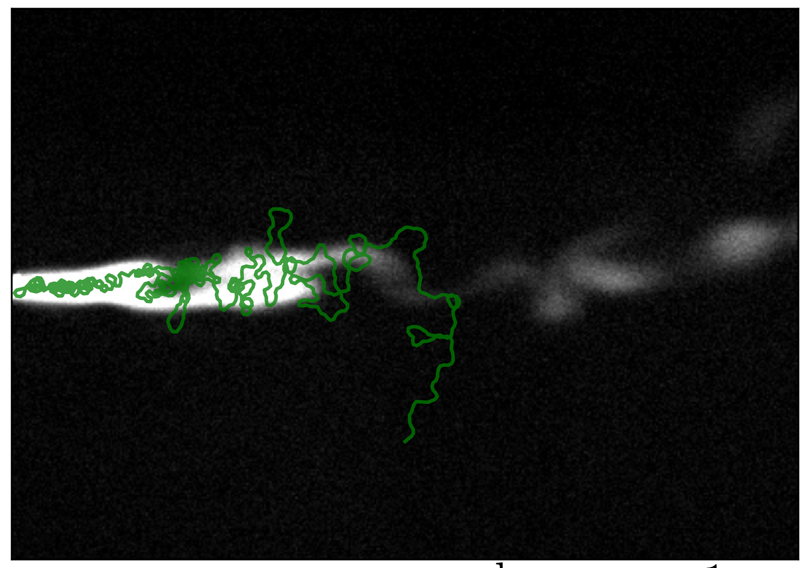


Temporal order contributes minimally to information.

Application to a model of binaral comparison

To show the utility of these cues, we constructed a simple model that is able to locate the odor source. The model is based on binaral comparison[3]. Odor concentration is binarized at the front end with an adaptive threshold. Left-right differences in weighted averages of previous odor samples determine turning behavior.





$$\dot{x} = v\cos(\theta),$$
$$\dot{y} = v\sin(\theta),$$
$$\dot{c}_{\text{thres}} = \left(0.5(c_{\text{hist,l}} + c_{\text{hist,r}}) - c_{\text{thres}}\right)/\tau,$$
$$\dot{c}_{\text{left,right}} = \beta\left(\frac{1}{1+e^{0.01(c-c_{\text{thres}})}} - c_{\text{left,right}}\right),$$
$$\dot{c}_{\text{hist(l,r)}} = \gamma\left(\frac{1}{1+e^{0.01(c-c_{\text{thres}})}} - c_{\text{hist(l,r)}}\right),$$
$$\dot{l}_p = \frac{1}{\tau_F}\text{abs}\left(\dot{c}_{\text{left}} - \dot{c}_{\text{right}}\right),$$
$$\dot{\theta} = \alpha\frac{\text{sig}\left(c_{\text{left}} - c_{\text{right}}\right)}{1+\exp\left(\dot{l}_p/0.01\right)},$$

where $v = 1$, $\tau = 0.1$, $\beta = 0.5$, $\alpha = \gamma = 1$, $\tau_F = 50$.

Conclusions

- Investing more than a few bits in concentration resolution yields diminishing returns.
- Multiple samples at lower resolution yield more information than one sample at high resolution.
- For each encoding scheme, there is a significant benefit of investing more than 1 bit per sample.
- Temporal sequence of measurements yields only minimal information.

Funding and References

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1 Crimaldi, J.P., Wiley M.B., Koseff J.R., The relationship between mean and instantaneous structure in turbulent passive scalar plumes

2 Shannon, C.E. (2001). A mathematical theory of communication. ACM SIGMOBILE Mobile Computing and Communications Review, 5(1), 3-55.

3 B. Ermentrout. Mathematics of Simple Olfactory Search. SIAM News, Vol 49, No 8, October 2016.