Olfactory navigation: how to make decisions using a broken signal

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BACKGROUND

During my second year of PhD I defined more precisely the focus of my reasearch: I extended the theoretical tools, inspired by hunting octopus, developed during my first year to a more general setting of olfactory search. In my research I try to understand how biological systems adapt to decode the sparse information brought by turbulence.

ALGORITHMS FOR INFERRING POSITION OF THE PREY FROM A DISTANCE

I developed fluid-dynamic simulations to reproduce the environment in which different animals live. I used the open-source software Nek5000 to generate a dataset of a realistic odor evolving in a turbulent channel $20m$ long (Figure 1.a). You can find more details about the numerical simulations I am performing in my first year PhD report.

I developed algorithms to understand how an animal can interpret this fluctuating signal to find its prey. Specifically, the objective of this second part of the work is to develop algorithms that take the odor signal obtained with my numerical simulations and provide distance as an output. To do this I use supervised learning, the technique is the same described in my first year report.

In my second year I focused my analysis on threshold modulation. In fact an important aspect of olfaction is that real sensory systems have finite sensitivity and in a noisy environment their measurements are imperfect. Only odor cues above a detection threshold can be sensed and algorithms for inference will depend on this detection threshold (Figure 1.b).

Biology inspired another improvement to our predictions: measuring and analyzing a complex signal is a difficult task; evolution shaped animal brain to simplify the task and maximize the extracted information. I tried to condense the odor signal my algorithm takes as input in individual scalar quantities, or features: average, intermittency, duration of blanks, duration of whiffs, slope of whiffs (Figure 1.c).

Figure 1: a) A snapshot of odor evolution in a turbulent channel. b) Only signal above a defined threshold is taken into account. c) To compute intermittency I binarize the signal, I count zero when it is below the threshold and one when above. I call "blanks" periods of time with no odor detections, while "whiffs" are periods of time of consecutive detections.

Odor localization is a linear problem: if you double the intensity of the source you will double the concentration in every spatial point, setting a threshold introduces a non-linearity in the problem. After some trials I developed an algorithm that automatically adapts the optimal threshold: it first takes into account the average threshold on a fixed temporal interval and then sets the local threshold as 0.5, 1 or 2 times the average threshold. Performance of individual features at different heights of the channel are reported in the figure below (Figure 2) and they allow to infer source location to some extent, but no single feature is reliable across different conditions.

Interestingly, processing the whole time course of the signal rarely performs better than our best features, suggesting that encoding the information in a single quantity may be preferable to storing odor concentration per se. Furthermore it is interesting to notice that average is well performing but it requires information about the intensity of the source, while the other considered features do not.

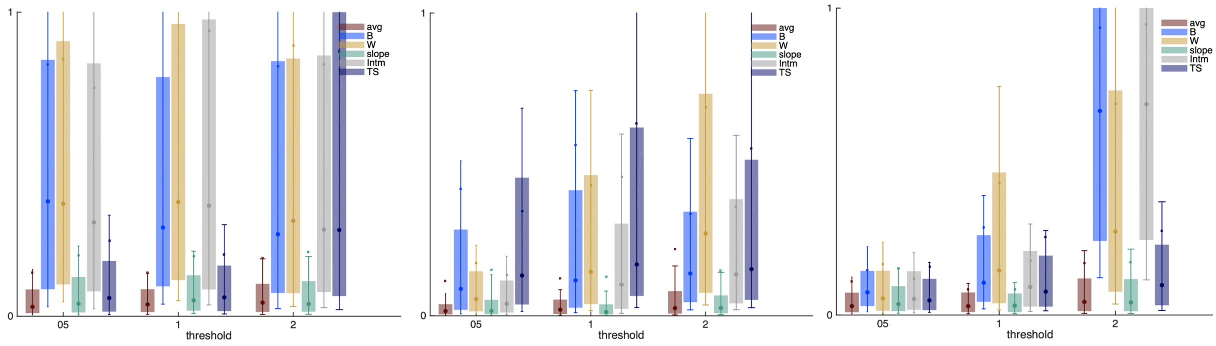

Figure 2: From left to right: performance of the different features at low height, middle height, large height.

I also concluded that performance improves as a function of memory, but memory does not affect the ranking among the different features. I explored what happens if you add a second dimension to the problem and I am currently investigating what happens combining different features together. As future perspectives our results suggest that low dimensional representations of the odor may efficiently define the state space for reinforcement learning applications.

EXPERIMENTAL APPLICATION

I am working in collaboration with Gire Lab (University of Washington) in order to apply my theoretical predictions to experiments. One first set of experiments has concluded this year and aims at understanding the role of glomeruli (a key part of mammal olfactory-neural system) when they are exposed to variation of odor flux and concentration. A second set of experiments has been recently planned and it will reproduce my theoretical prediction in a controlled setup, where the animals will be able to smell an intermittent odor pattern from a far away source. The source will be located in different positions, and the animal will try to infer the correct location, brain activity will be monitored simultaneously.

References

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1 Attended courses

- Quantum Phase Transition (passed the exam)
- Computazione Quantistica
- Advanced Computational Physics (passed the exam)
- La Matematica del Machine Learning (passed the exam (x2))
- Boulder School 2019: Theoretical Biophysics (passed the exam)