

Navigation by hunting octopuses: how to make decisions using a broken signal

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BACKGROUND

Biological systems are surrounded by fluids and evolved spectacular adaptations to decode the sparse information brought by turbulence. Fluids disperse unpredictably a large number of chemicals: different animals can exploit odor plumes to acquire information about the surrounding environment. Decoding olfactory signals is fundamental to locate food, conspecifics and to avoid predation: how do animals localize the source of the odor? Which kind of algorithms drive their search? Many investigations on rodents and flies have been realized [1], my research approaches a different branch of animal kingdom: cephalopods, in particular octopuses. My research project focuses on octopuses hunting in the ocean: they localize their prey using turbulent odor, water movement and pressure. I model octopuses and their environment using statistical fluid dynamics and decision theory.

My project started from observations of octopuses hunting in a large tank: they reach their prey in one shot as they exactly knew its location. This behavior is enabled by a peculiar nervous system: their entire body is in fact covered by many chemo-receptor and most neurons are distributed in the arms and only the remaining 1/3 in a central brain: how many and which decisions are made globally vs locally is still unclear. We aim at understanding how can a macroscopic agent, receiving a complex odor signal, infer where is the prey. To answer this question we need to (1) understand what is the signal; (2) develop algorithms able to take signal as input, and provide distance as output.

(1) FLUID DYNAMICS SIMULATIONS

The first goal of my PhD is to simulate a turbulent flow in which a realistic odor field spread from a source. This odor field will then be used by an agent to infer the location of the source. In my simulations a scalar (odor) evolves in water from a localized source (prey). Odor is an intermittent quantity that spreads from the source disgregating in fluctuating puffs. The shape of these intermittent puffs changes as they are deformed by the turbulent flow far from the source. An organism will detect odor within a conical volume which is the typical shape of the plume in olfactory searches [2]. I solved incompressible Navier Stokes equations (1) and passive scalar equation (2) numerically using the open source solver Nek5000:

$$\partial_t u + u \cdot \nabla u = -\frac{1}{\rho} \nabla P + \nu \nabla^2 u + f \quad \nabla \cdot u = 0 \quad (1)$$

$$\partial_t \theta + u \nabla \theta = D \nabla^2 \theta \quad (2)$$

the fluid domain is divided in discrete elements, in every element the code expands the solution in 8th grade polynomials.

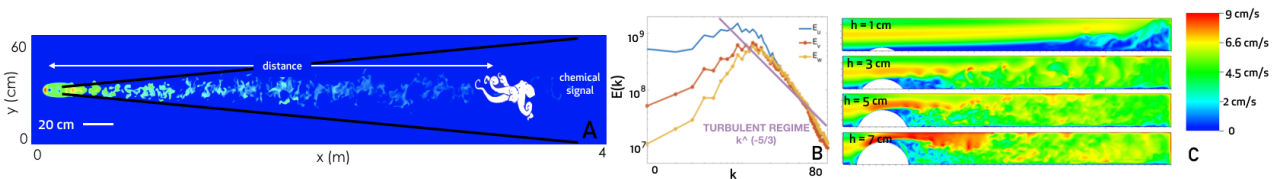


Figure 1: Statistics of the odor signal.

Water is moving from left (inlet) to right (outlet), see snapshot of odor in Figure 1A. The Reynolds number, defined as $Re = \frac{UL}{\nu}$ represents the ratio of inertial forces to viscous forces. In my simulations the Reynolds number is ~ 6000 which is expected to be turbulent [3]. I implemented a spherical cap at the inlet of the domain, increasing/lowering the cap allows me to tune velocity fluctuations and then to control turbulence in the box (see Figure 1C). To mimic the ocean floor, where the octopus lives, I used outflow boundary condition on the top sides and outlet; these correspond to setting the normal component of the stress tensor derivative equal to zero. This choice makes the odor evolution in my finite domain consistent with an infinite domain,

where only a small portion is taken into account [4]. I verified that at these Reynolds numbers the odor and flow are turbulent (Figure 1B shows that the spectra are consistent with the $-5/3$ power law expected for turbulent signals [5]). The intensity of fluctuations in velocity scaled with the mean flow increases when the obstacle is larger, because the mean flow impacting the obstacle causes turbulence. I observe the well known cone of detection, i.e. that odor is only present within a cone with aperture v/U , where v is the magnitude of the velocity fluctuations and U is the mean flow (Figure 1A).

(2) ALGORITHMS FOR INFERRING POSITION OF THE PREY FROM A DISTANCE

I am currently developing algorithms to understand how can an octopus 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 (see sketch in Figure 1). To do this I use supervised learning. At a fixed spatial position odor concentration varies in time, the algorithm takes this time-varying signal as an input and predicts the distance from the source. I implemented a supervised learning algorithm: I search for a function $f : x \rightarrow y$, where x are input data (odor) and y are output data (distances). I use a portion of my simulations to train the algorithm, i.e. to find the function f that minimizes the sum of square errors $[f(x) - y]^2$ plus a term that imposes regularity of the function. This term is known as a regularizer that avoids overfitting (namely perfectly reproducing the training dataset but failing in reproducing a different one), and I choose to use Tikhonov regularization [6]. I then test the performance of the function f with a new set of data, that have not been used for training. This is called the generalization error. In order to implement this algorithm, assumptions over f are needed. I use a Kernel method that corresponds to writing f as an infinite sum of basis function. This method is particularly powerful in that the function f is non-linear in x , and the method applies easily to vectorial input spaces. This is important because my input is vectorial: my x is the time-varying odor field in discrete space-time points.

Simple inferences can be accomplished by averaging over the body of the octopus or over time and also setting a threshold on the odor concentration helps the animal in improving its performance. However I showed that time series contain much more information than simple averages. To prove these points, I first averaged the time-varying signal over space in a disk of given radius, hence x is now a scalar (average odor) and f infers a scalar y (distance). Performance in the case where x is the space average only is poor (Figure 2A shows the predicted vs correct distance and the average generalization error normalized to variance of y). Performance improves when x is the space and time average (Figure 2B) and when x is the space average of odor above a threshold (Figure 2C). I then considered the full time varying signal (or time series), hence x is now a vectorial input containing odor at each instant in time. Performance of the algorithm improves considerably (Figure 2D), indicating that the time series contains much more information than simple averages. I have considered different time spans, and found out that there is an optimal length of the vectorial input (or optimal memory) to maximize performance (Figure 2E).

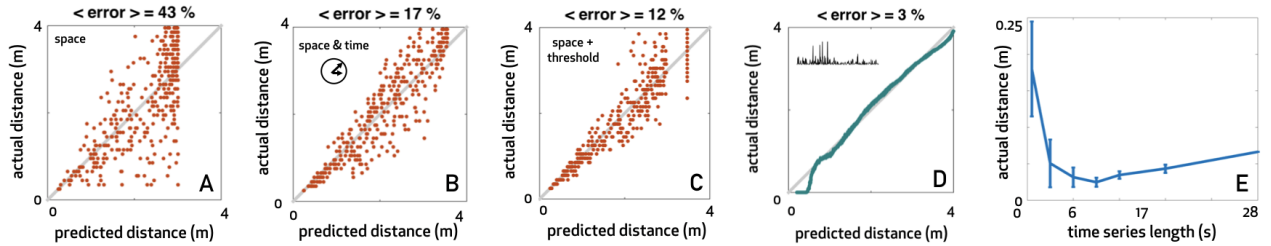


Figure 2: Performance of supervised learning algorithm for different design of the input data.

I am currently proceeding in three directions. (1) Understand the reason for this optimal memory. Is this linked to the statistical learning problem? Or is it connected to the physical properties of the odor signal? (2) What are the features of the odor time course that are more useful for this problem? This is a classical problem in machine learning and signal processing, and essentially involves finding the best filters to represent the signal in a smaller dimensional space. (3) Does sensing pressure improve performance? This last question is motivated by experimental observations performed by our collaborators.

EXPERIMENTS

I am working in collaboration with neurobiologists from University of Washington (Seattle) that perform experiments with octopuses. They observed that moving preys are favored by octopuses, which motivates our question above. However, in practice, decoupling chemical, mechanical and visual cues is difficult, which sense is

bringing more information about the location of the prey? Few behavioral experiments have been realized with octopuses and the question is still open. I proposed a series of new experiments (scheduled in the next months) to answer these question (see Figure 3). Once we will know what are the sensory signals used by octopuses during hunting, we will be able to add mechanical cues to our algorithms. Experiments will use a 3D-printed crab (tests for tactile cues only - left panel); a dead crab (testing for tactile and chemical cues - mid panel); and finally a live crab (testing for mechanical, tactile and chemical cues - right).

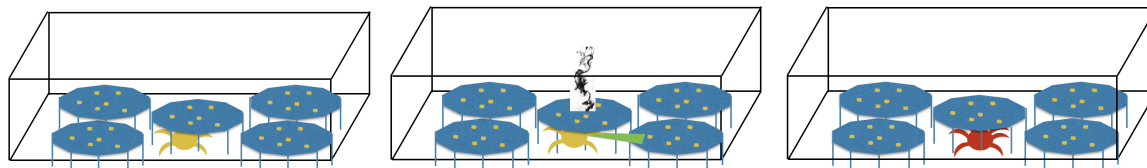


Figure 3: **Proposed experiments:** we will image an octopus reaching prey in a tank where the floor is covered by a structure with small crevices that does not allow the animal to see what is underneath, the animal can explore what is below the structure using its arms.

References

- [1] Baker KL et al. Algorithms for Olfactory Search across Species. *J Neurosci.* 38(44):9383–9389 2018.
- [2] Celani A. et al. Odor Landscapes in Turbulent Environments, *Phys.Rev.X* 4, 2014.
- [3] N. Marati et al. Energy cascades and spatial fluxes in wall turbulence. *J. Fluid Mech.* vol. 521, pp. 191–215 2004.
- [4] S. Dong A Convective-like Energy-Stable Open Boundary Condition for Simulations of Incompressible Flows. *J Comput Phys*, 302, 300 2015.
- [5] U. Frisch. Turbulence: The Legacy of A. N. Kolmogorov. Cambridge University Press. 1995
- [6] C. E. Rasmussen, C. K. I. Williams, Gaussian Processes for Machine Learning, the MIT Press, 2006

1 Attended conferences

- Fluids and complexity *Dec 2018 Nice (France)* [1]
- Waves Cote d’Azur *Jun 2019 Nice (France)* - **presented a poster**, *best poster award winner* [2]
- Boulder School 2019: Theoretical Biophysics *Jul 2019 Boulder (USA)* - **presented a poster** [3]
- Making sense of turbulence, Q-Bio meeting *Harvard University (USA)* - [4]

2 Attended courses

- A short course on integrable PDEs: the KdV and other equations. (U. Nice J. D. Gibbon) [no exam]
- Advanced Computational Physics
- La Matematica del Machine Learning
- Boulder School 2019: Theoretical Biophysics
- PhD course on the Physics of turbulent flow (U. Nice - Jeremie Bec) [no exam]