



When poor little fish meet AI, VR, robots, and drones!

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G. Theraulaz, R. Escobedo (CRCA, Toulouse)

F. Mondada, V. Papaspyros (EPFL): AI, LureBot

P. Mitra (CSHL): Al without networks

S. Sanchez (IRIT), R. Bastien (CRCA): VR for Fish

L. Lei (University of Shanghai): Cuboid Robots

G. Hattenberger, M. Verdoucq (ENAC): Drones



Collective motions of animals and robots – 27-31 May 2024 – Cargèse





Outline



Generative models for collective motion

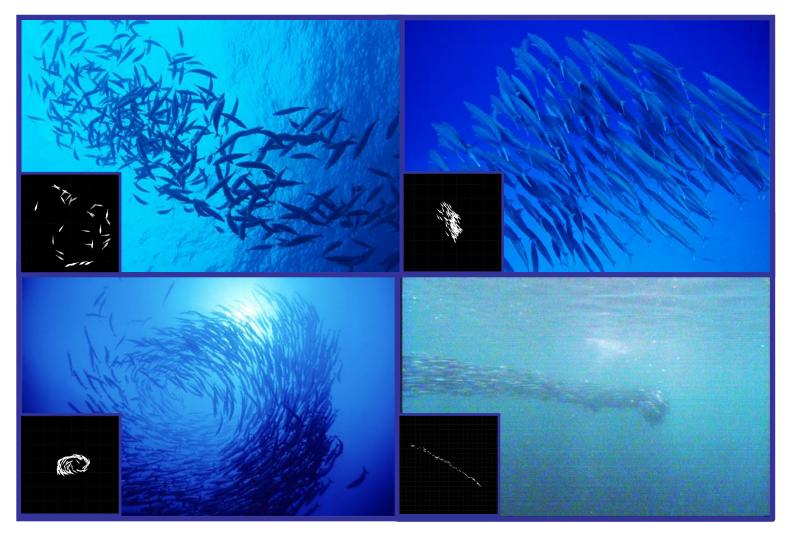
- Analytical models exploiting the reconstruction of the interactions with obstacles and conspecifics (+simplified interaction with the fluid)
- >Machine learning models trained on real trajectories
- Kernel interpolation models

≻3 applications of generative models

- ≻The LureBot
- ≻VR for fish
- ➢Drones

Collective motion in fish schools

Swarming, schooling, milling



Measuring social interactions

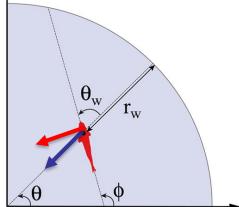




How to measure the fish interaction with the wall?

$$\delta\phi = \delta\phi_{\rm Random} + \delta\phi_{\rm W}$$

$$\delta\phi_{\rm W} = f_{\rm w}(r_{\rm w}) \times O_{\rm w}(\theta_{\rm w})$$



where $O_w(\theta_w) \sim \sin(\theta_w)$ is an *odd* function of θ_w

Minimize
$$\Delta = \sum_{n=1}^{\# \text{data}} \left[\delta \phi_n - f_w(r_{w,n}) O_w(\theta_{w,n}) \right]^2$$

(tabulating f_w and O_w on a grid for the r_w and θ_w variables)

PLOS Comp. Biol. 2018 Phil. Trans. 2020

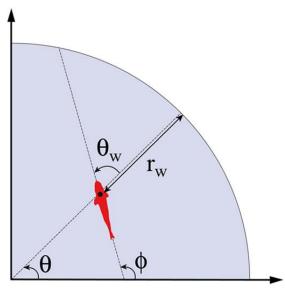
Measuring interactions for Hemigrammus

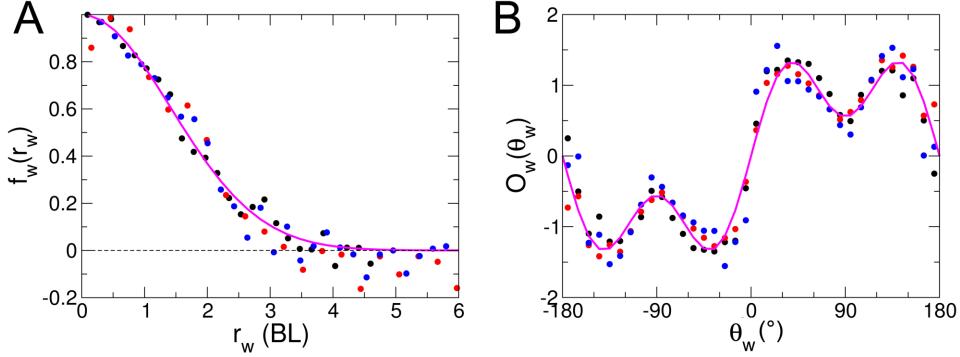
Interaction with the wall

$$\delta\phi_{\rm W} = f_{\rm w}(r_{\rm w}) \times O_{\rm w}(\theta_{\rm w})$$

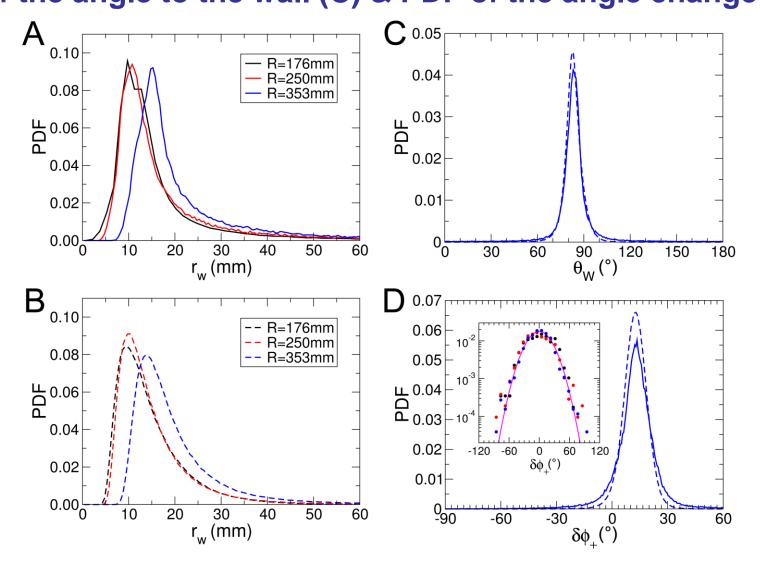
$$f_{\rm w}(r_{\rm w}) \propto \exp[-(r_{\rm w} / l_{\rm w})^2], \ l_{\rm w} \approx 2 \,\mathrm{BL} \sim 60 \,\mathrm{mm}$$

$$O_{\rm w}(\theta_{\rm w}) \propto \sin \theta_{\rm w} [1 + \epsilon_2 \cos 2\theta_{\rm w}], \ \epsilon_2 \approx 0.7$$





1-fish experiments vs model (dashed lines) PDF of the distance to the wall (3 arenas; A & B); for R=353 mm, PDF of the angle to the wall (C) & PDF of the angle change (D)

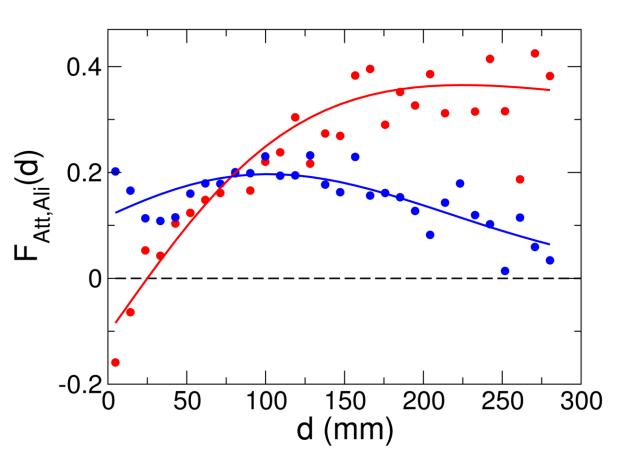


Measuring interactions in Hemigrammus

Attraction and alignment interactions between fish vs their distance

$$F_{\text{Att}}(d) \propto \frac{(d-a)/l_{\text{Att}}}{1+(d/l_{\text{Att}})^2}, \qquad F_{\text{Ali}}(d) \propto \left(\frac{d}{l_{\text{Ali}}}+c\right) \exp[-(d/l_{\text{Ali}})^2]$$

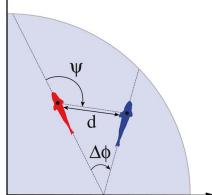
 $l_{Att} \approx l_{Ali} \approx 200 \,\mathrm{mm}$ $a \approx 1 \,\mathrm{BL} \approx 30 \,\mathrm{mm}$ $c \approx 0.4$



Measuring interactions in Hemigrammus

Attraction and alignment interactions between fish vs viewing angle and relative heading

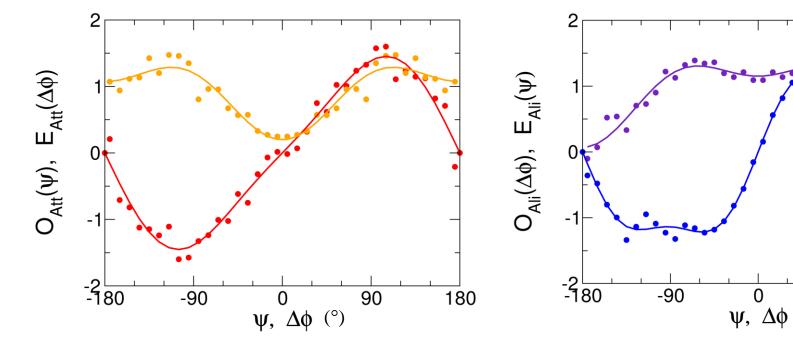
$$\delta\phi_{\text{Att}} = F_{\text{Att}}(d) O_{\text{Att}}(\psi) E_{\text{Att}}(\Delta\phi)$$
$$\delta\phi_{\text{Ali}} = F_{\text{Ali}}(d) O_{\text{Ali}}(\Delta\phi) E_{\text{Ali}}(\psi)$$
$$(O = \text{Odd}; E = \text{Even})$$



180

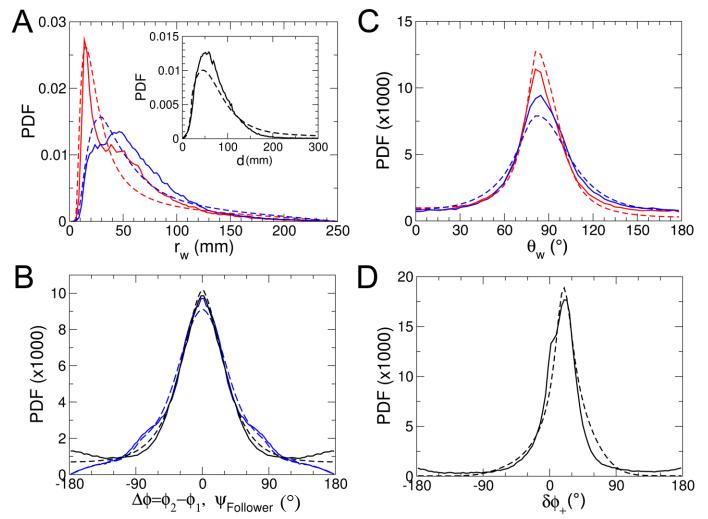
90

(°)



2-fish experiments vs model (dashed lines)

PDF of the distance (A) and angle (C) to the wall (leader vs follower); PDF of the heading difference (B; black) and the follower angle of view (B; blue), and of the angle change (D)

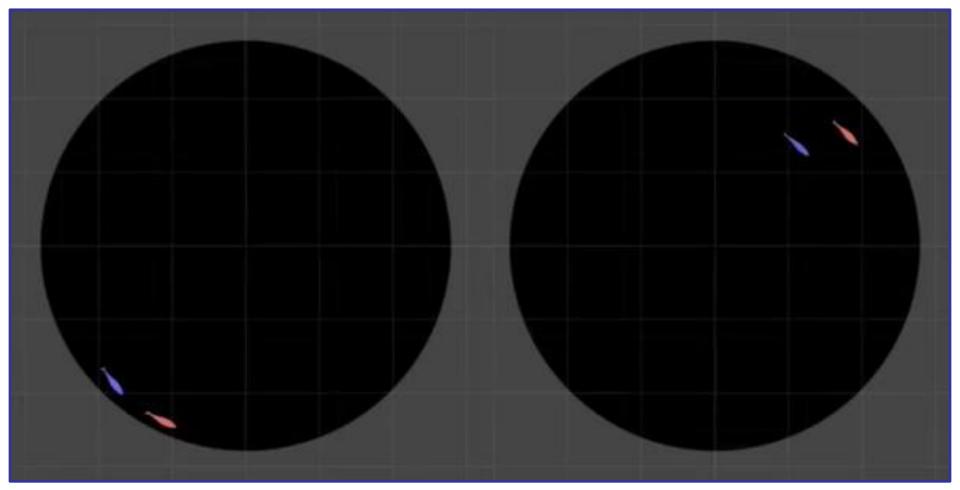




Model vs experiment ("Turing test")

Experiment

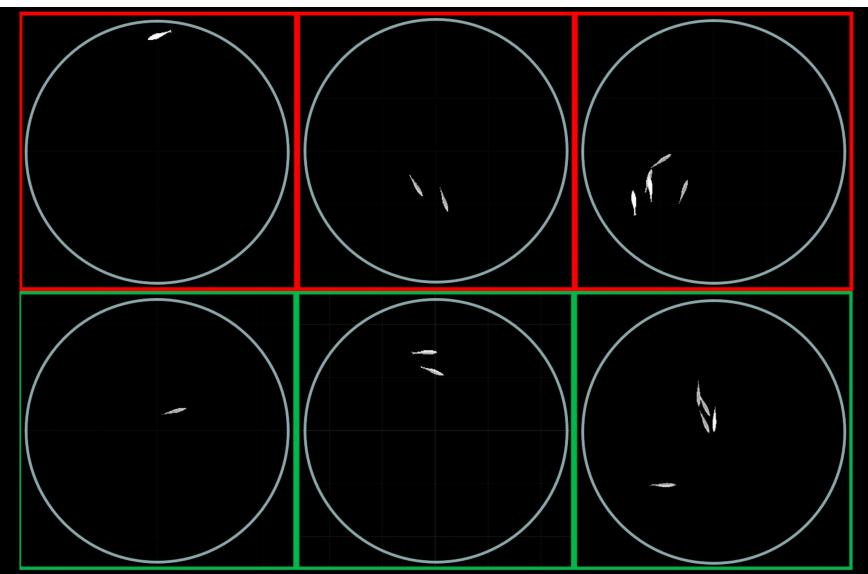
Model simulations





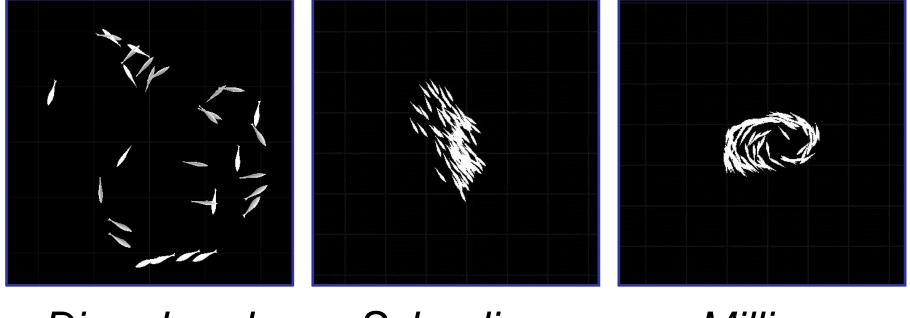
Model vs experiment ("Turing test")

Experiments vs model simulations





Collective phases in fish schools



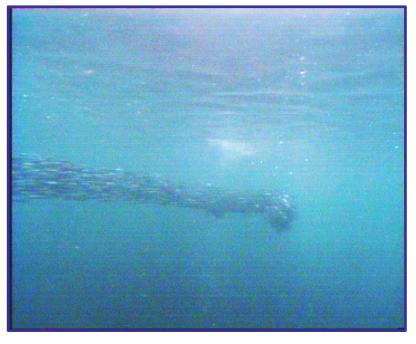
Disordered

Schooling

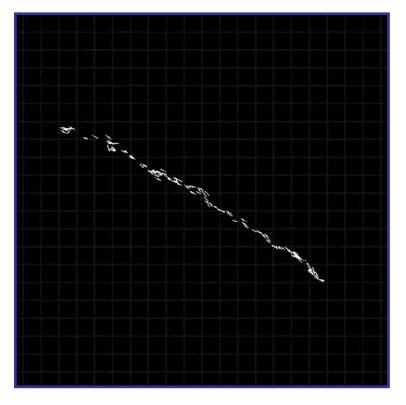
Milling



The elongated phase



School of herrings (Clupea harengus) Photo P. Brehmer - IRD

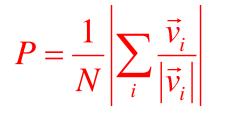


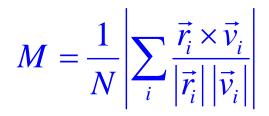


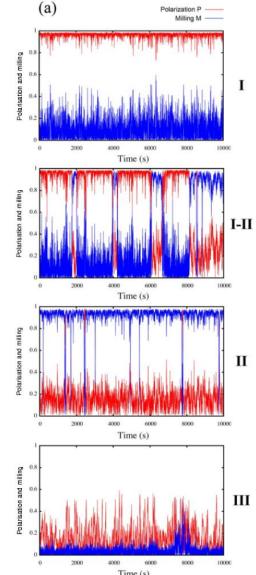
Phase diagram for fish schools

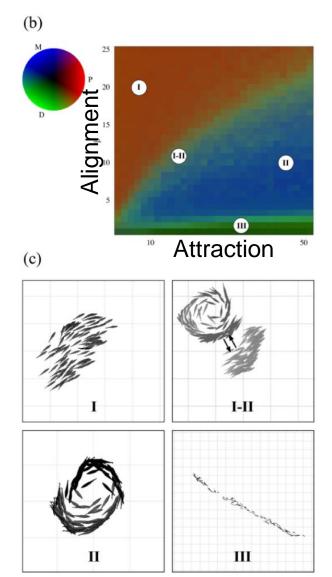
New J. Phys. 2014; J. Roy. Soc. Interface 2015; PLOS Comp. Biol. 2022

Order Parameters











Phase diagram for fish schools

Behavioral model coupled to a simple fluid model (with C. Eloy, E. Kanso, et al.) Phys Rev. Lett. 2018

Fish seen as fluid dipole: transported by the resulting velocity field, and rotated by the local velocity gradient

≻Main results

The phase diagram is very similar to that of the behavioral model + "turning phase"

The fish move **faster** in an ordered state

Ordered schools acquire some internal structure

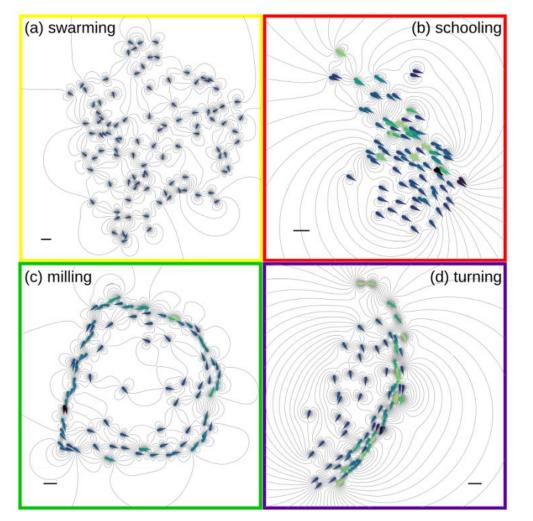
The fluid velocity fluctuations act similarly to the "cognitive noise" in the behavior model



Phase diagram for fish schools

Phys Rev. Lett. 2018

Behavioral model coupled to a simple fluid model (with C. Eloy, E. Kanso, et al.)





Deep learning "models" of fish

ML model reproducing short- and long-term fish dynamics
The structure of the network includes some biological insight
Straightforward to train with other species
Possibility to open the ML "black box" in this context

Predicting long-term collective animal behavior with deep learning

V. Papaspyros^{1*}, R. Escobedo³, A. Alahi⁴, G. Theraulaz³, C. Sire^{2*}, F. Mondada¹

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² Laboratoire de Physique Théorique, CNRS, Université de Toulouse — Paul Sabatier

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Hilbert interpolation scheme (with P. Mitra)

Consider *n* (training) configurations C_i of a system, corresponding to some observable O_i

- C = pixels of an image; O = classifier
- C = position / velocity of N fish; O = acceleration of the N fish

$$\hat{O}(C) = \sum_{i=1}^{n} w_i(C) O_i, \quad w_i(C) = \frac{\|C - C_i\|^{-d}}{\sum_{j=1}^{n} \|C - C_j\|^{-d}}, \quad d = \dim(C)$$

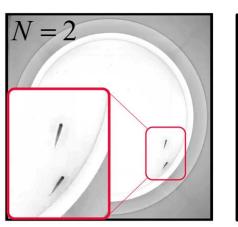
Many rigorous mathematical results

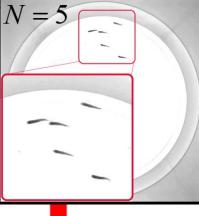
• Statistical consistency with a prediction error $\sim 1/\ln(n)$

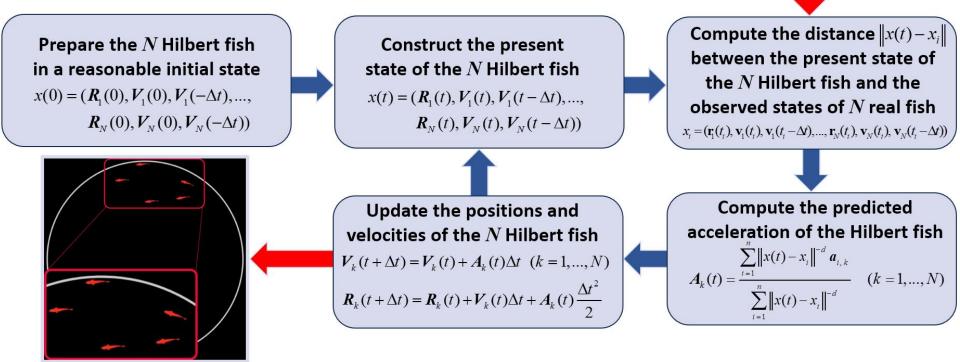
• . . .

Interpolation "models" of fish (with P. Mitra)

Implementation flowchart of Hilbert Interpolation as a fish trajectory generative model







Interpolation "models" of fish (with P. Mitra)

>No training phase!

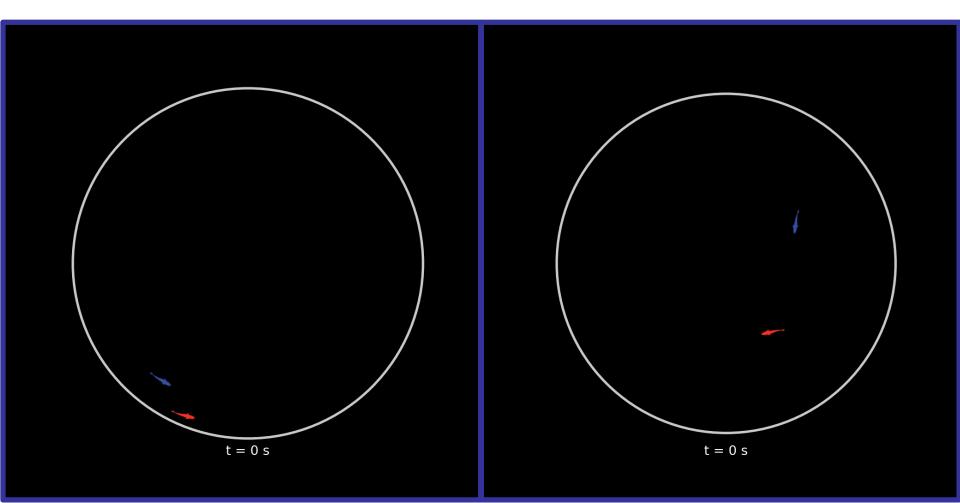
Explicit formulation without any parameter
Like ML, straightforward to apply to other species
Like ML, can augment the experimental dataset
Like ML, interpolation models are only generative

Interest of our scheme in the scientific context:

- Straightforward to implement/code and to port/share
- Strictly **reproducible** results
- Update/create the training dataset live (robotic applications)
- Credit assignment: evaluate the relative importance of different experimental configurations (the most typical and the most biologically relevant)

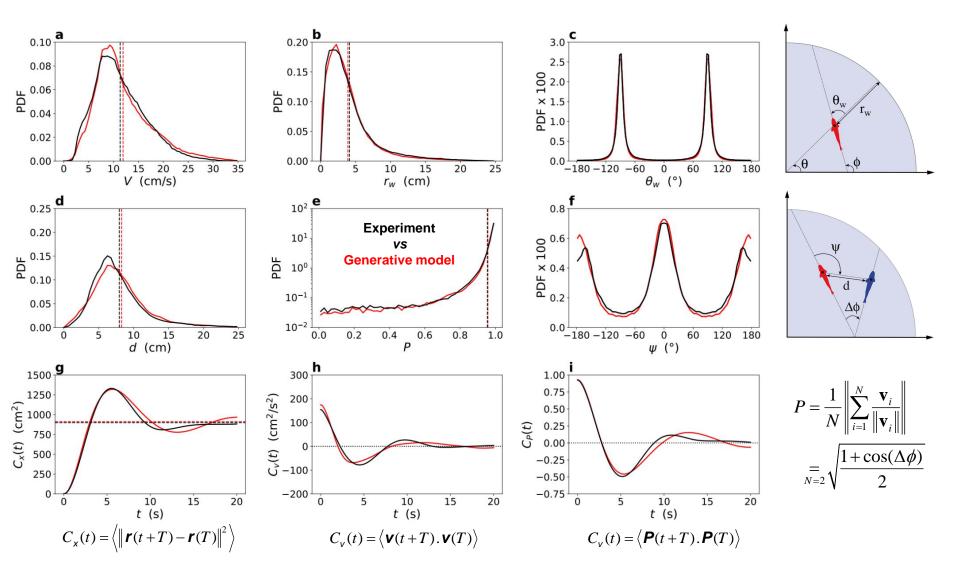


The Hilbert fish have learned the presence of the wall



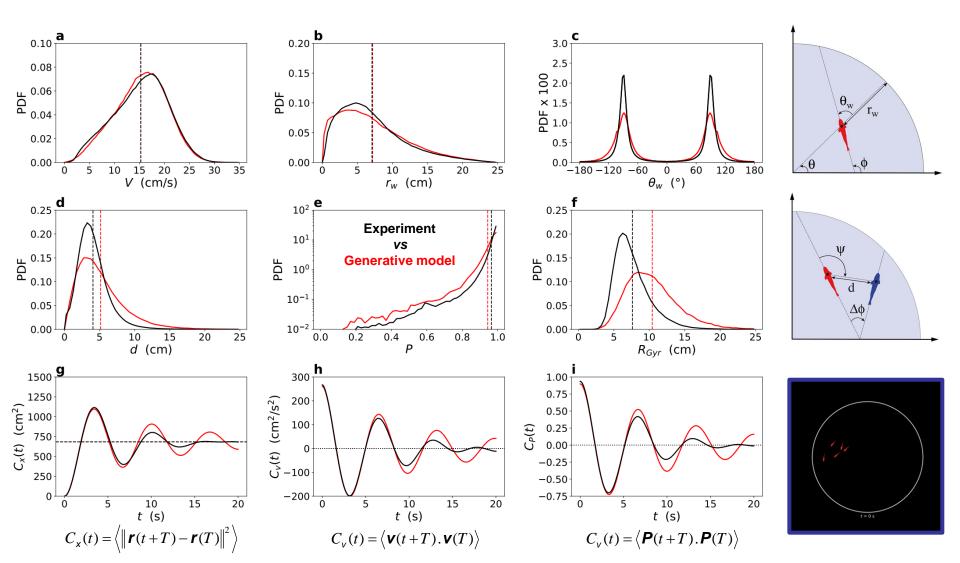
Interpolation "models" of fish (with P. Mitra)

Quantification of the agreement with experiment for 2 fish





Quantification of the agreement with experiment for 2 fish



Interpolation "models" of fish (with P. Mitra)

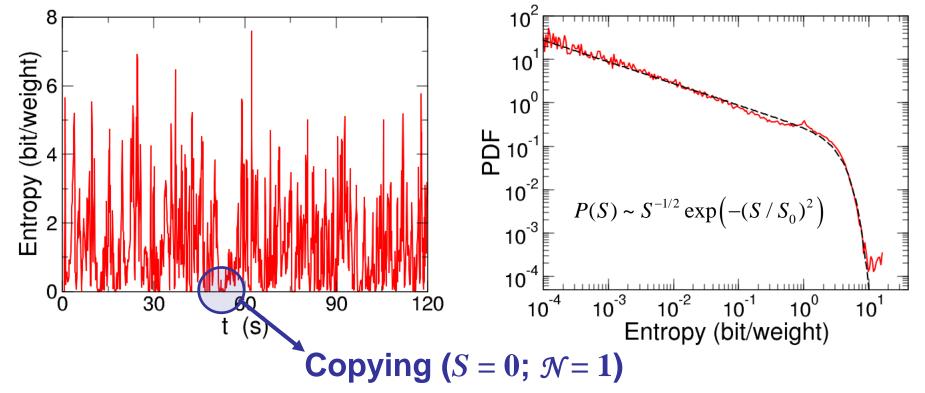
Entropy of sampled configurations

$$\geq S(t) = -\sum_{i=1}^{n} w_i(\boldsymbol{x}(t)) \log_2 \left[w_i(\boldsymbol{x}(t)) \right]$$

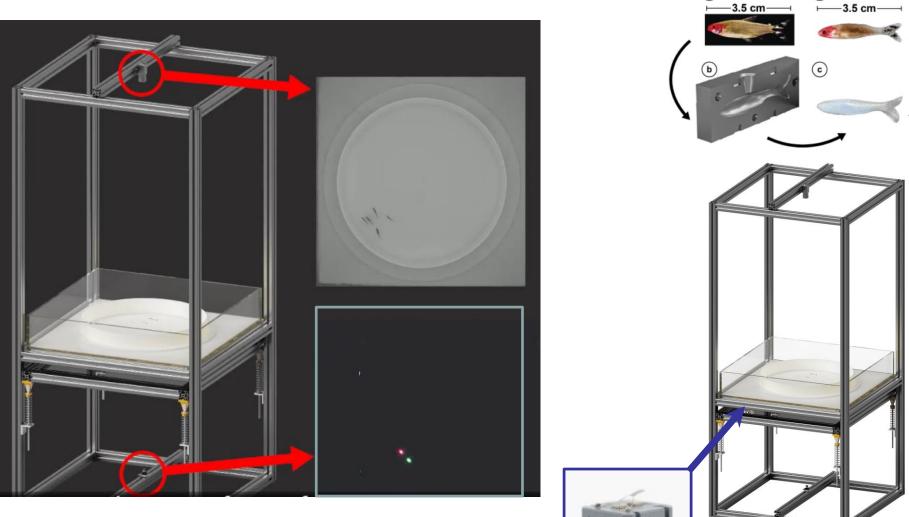
 \succ Quantifies the effective number of data used for the prediction: $\mathcal{N} = 2^S$

The weights allow to asses the most typical and biologically relevant configurations

 $\gg \mathbb{E}[S] \sim \log_2(\sqrt{n})$ in the pure regression context









(a)

(d)



Fish model implemented in the LureBot

A biohybrid interaction framework for the integration of robots in animal societies V. Papaspyros^{1*}, D. Burnier¹, R. Cherfan¹, G. Theraulaz², C. Sire³, F. Mondada¹ ¹ Mobile Robotic Systems (MOBOTS) group, École Polytechnique Fédérale de Lausanne (EPFL) ² Centre de Recherches sur la Cognition Animale, Centre de Biologie Intégrative, CNRS, Université de Toulouse — Paul Sabatier ³ Laboratoire de Physique Théorique, CNRS, Université de Toulouse — Paul Sabatier * Corresponding author: vaios.papaspyros@epfl.ch EPF TIONAL SUISSE ZERISCHER NATIONALFONDS NAZIONALE SVIZZERO SWISS NATIONAL SCIENCE FOUNDATION

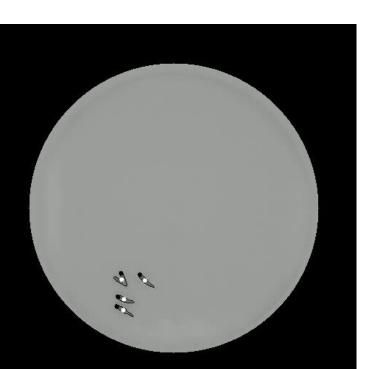
IEEE Access 2023; Bioinspiration & Biomimetics 2024

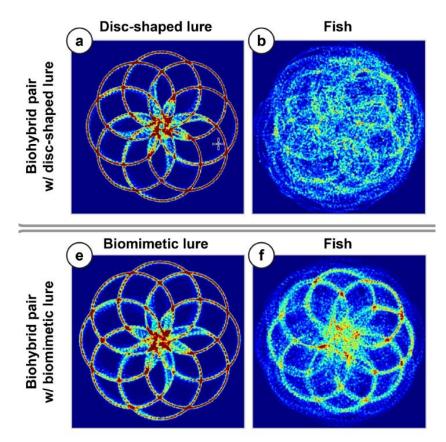


Fish model implemented in the LureBot

The LureBot is very well accepted by the fish

- Need to measure the fish-LureBot interactions
- A controlled perturbation to study fish schools

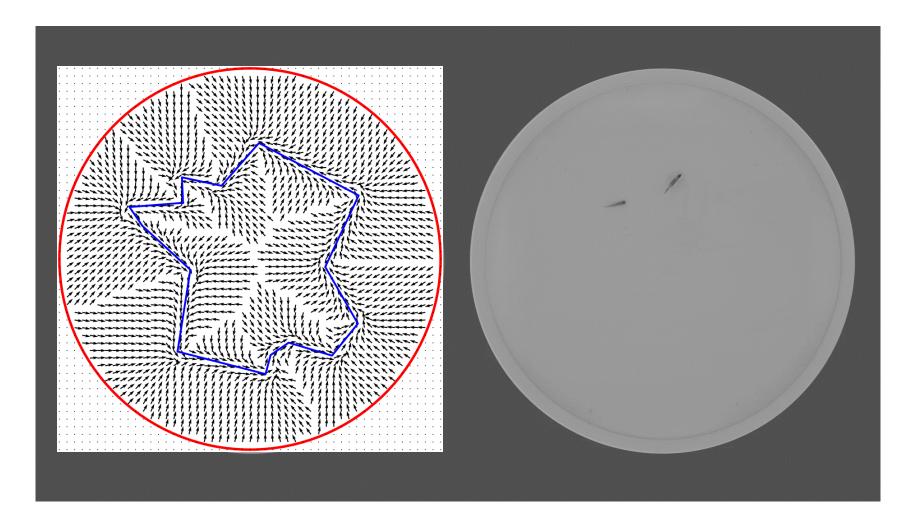




Density heat maps for the passive lure (disc-shaped or biomimetic) and the fish

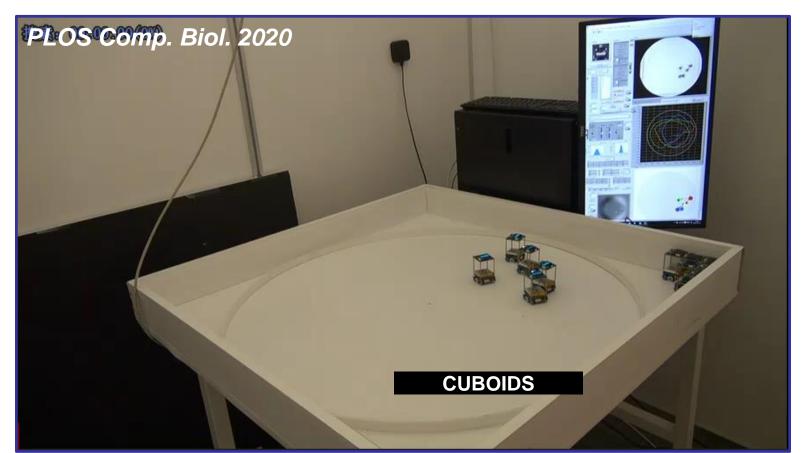


The LureBot and one fish in a "binational" fluid flow



Fish model implemented in the CUBOID robots

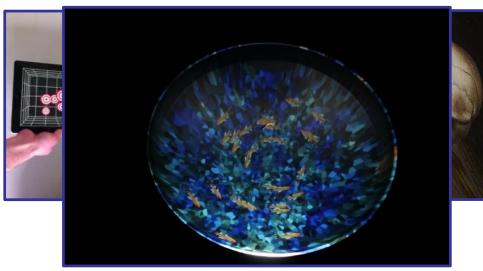
- Literal implementation of the fish model... but confronted to real-life physical constraints
- The main point of this work was actually to understand how animals combine their interactions (notion of most influential neighbors)





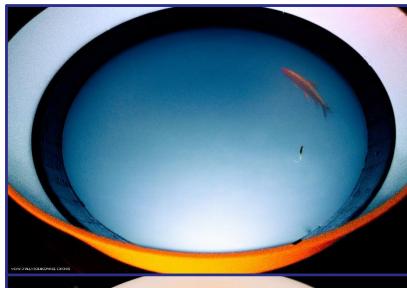
VR for Fish (ANR VR-FISHSCHOOL – CRCA-LPT-IRIT)

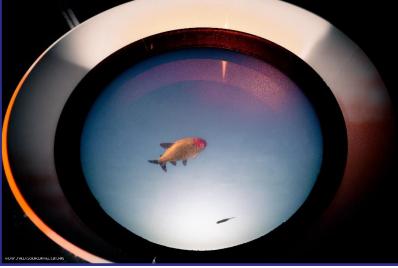
Realistic-looking lures are projected on the side of the bowl in anamorphic view



> 3D tracking of the fish to feed the "3D" model driving the VR-fish in closed loop

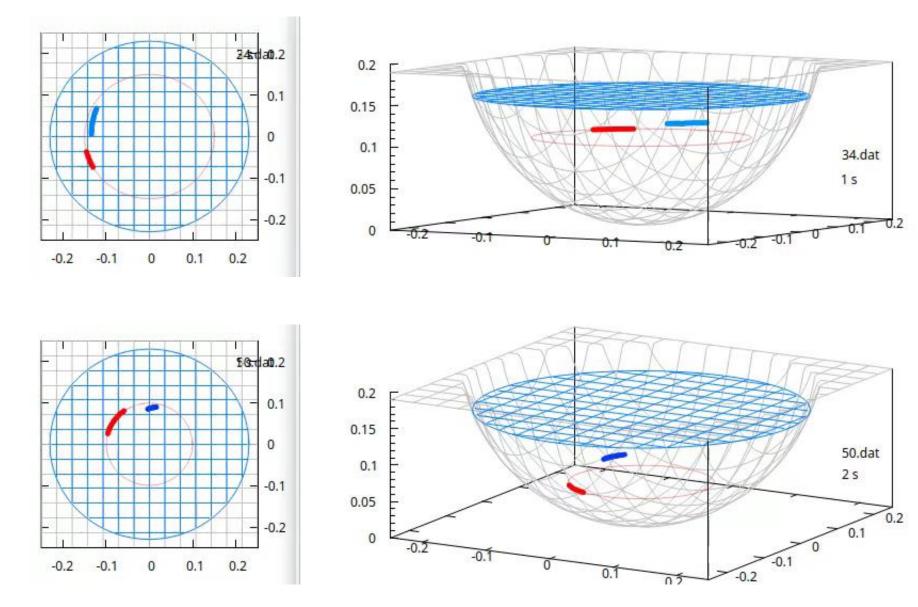
A tool to study the behavior of one fish in a (VR) school and to probe its response to controlled perturbations (complementary to the LureBot)







VR for Fish (ANR VR-FISHSCHOOL – CRCA-LPT-IRIT)





Bio-inspired 3D model implemented in drones



Bio-inspired 3D flocking algorithm with minimal information transfer for drones swarms

Matthieu Verdoucq (1,2), Clément Sire (3), Ramon Escobedo (2), Guy Theraulaz (2), and Gautier Hattenberger (1)

1: Ecole Nationale de l'Aviation Civile, Université de Toulouse, 31400 Toulouse, France 2: Centre de Recherches sur la Cognition Animale, Centre de Biologie Integrative (CBI), Centre National de la Recherche Scientifique (CNRS) & Université Paul Sabatier, 31062 Toulouse, France 3: Laboratoire de Physique Théorique, CNRS & Université de Toulouse Paul Sabatier, 31062 Toulouse, France

IEEE ICUAS (2022) & IROS (2023)



Bio-inspired 3D model implemented in drones (with Dronisos)





We also force invite humans to swim walk in a circular tank arena

(But we do not plan – yet – to make them interact with AI or robots, or fly drones)



Phil. Trans. Roy. Soc. 2020; PLOS Comp. Biol. 2021; J. Roy. Soc. Interface 2021; PNAS 2017 & 2023



Conclusion

- The study of collective phenomena in animal groups is taking advantage of the rapid progress in technology (real-time tracking; AI; response of a fish school to a (Lure)bot; response of single fish to a VR-school; drones...)
- Reconstruction and modelization of social interactions... but which must also adapt to real-life physical conditions and constraints
- Biomimetic inspiration for robots/drones: no need to implement the actual forms of animal social interactions in robots/drones... but they can still provide neat ideas in this robotic context
- A very interdisciplinary research (ethologists, computer scientists, roboticists... and a theoretical physicist!)



Conclusion

- 1 and 2 fish experiments (~45h and ~30h of data used)
- Characterization of the spontaneous burst-and-coast swimming
- Unprecedented characterization (exploiting symmetries) and precision measurement of the fish-wall and fish-fish interactions
- "Repulsion" of the wall: Gaussian dependence with the distance to the wall; "comfort" angle of 85°; burst-and-coast swimming nonetheless forces a fish to remain close to the wall
- Short distance repulsion (~1 BL) and long-range attraction (vision?) between fish; alignment interaction dominates up to 2.5 BL and then vanishes; attraction and alignment interactions modulated by viewing and relative heading angles; leader vs follower
- Explicit model guiding the data analysis and in good qualitative (videos) and quantitative (various PDF) agreement with experiments