Data-driven modeling of collective behavior in schooling fish

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Acknowledgements

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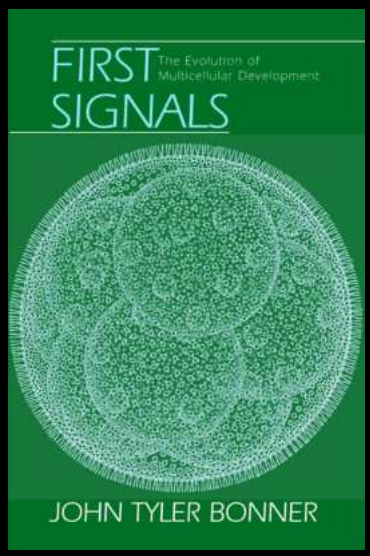
Collective motion in groups of organisms

Looking for coordination mechanisms in biological systems

Sturnus vulgaris

Collective motion in groups of organisms

Looking for coordination mechanisms in biological systems

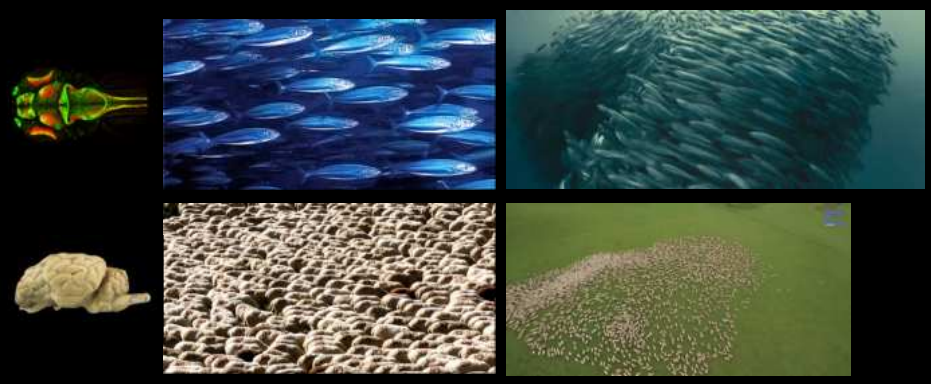


"One element that must have been equally important in distinguishing the living from the inert is the invention of a stimulus-response system", J.T. Bonner (1920-2019)

Collective motion in groups of organisms

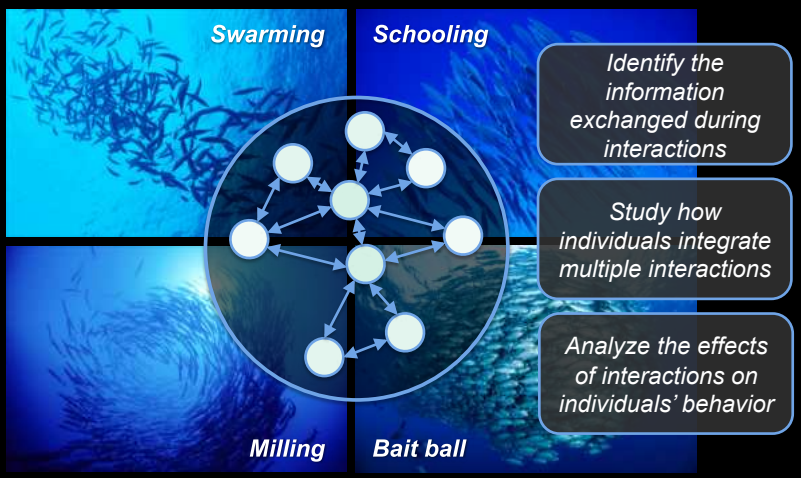
Looking for coordination mechanisms in biological systems

- Sensory and cognitive equipment together with environmental constraints shape social interactions involved in coordinated collective movements



Collective motion in fish schools

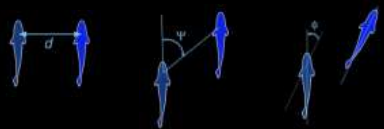
Collective patterns emerging from interactions between fish



Lopez, U. *et al.*, *Interface Focus* (2012)

How do group-level properties emerge?

Automated tracking of animal movement and behaviour



Distance *Angular position* *Relative heading*

Hemigrammus rhodostomus

Pérez-Escudero, A. *et al.*, *Nat. Methods* (2014)
Lecheval, V. *et al.*, *Proc. R. Soc. B* (2018)

Deciphering interactions in fish schools

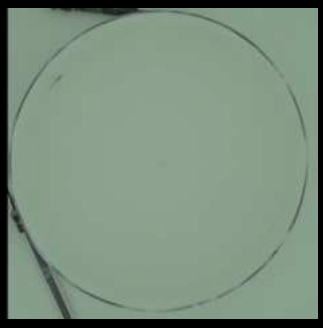
Study species: the Rummy-nose tetra

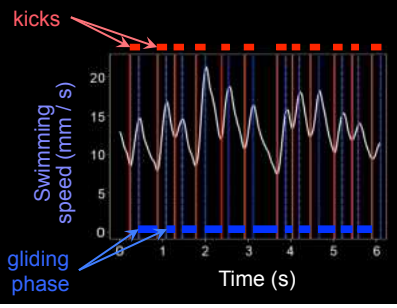
Hemigrammus rhodostomus

Average body length: 31mm

Analysis of individual swimming behavior

Burst-and-coast swimming



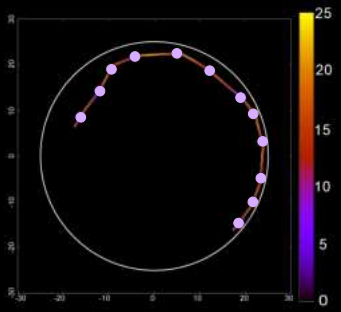


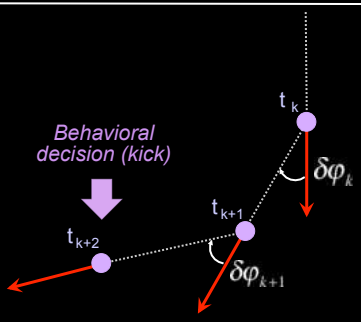
- *Hemigrammus rhodostomus* performs burst and coast swimming
- Each monotonous increase of velocity higher than 1cm/s is identified as a « kick »

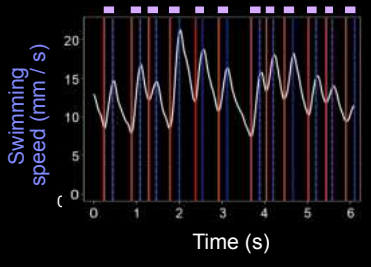
Calovi, D.S. *et al., PloS Comp. Biol.* (2018)

Analysis of individual swimming behavior

Segmenting the trajectories







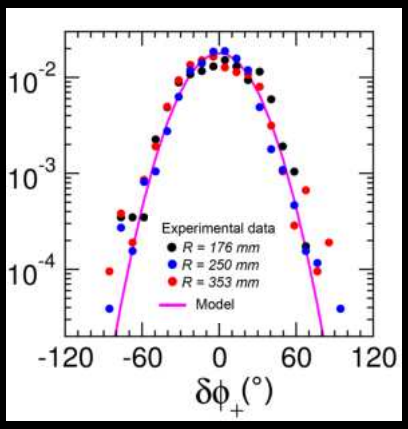
- Changes in fish heading occur at the onset of the acceleration phase
- The spatial locations where the fish has performed a kick can be used to identify the potential stimuli in the neighborhood that have triggered its behavioral responses

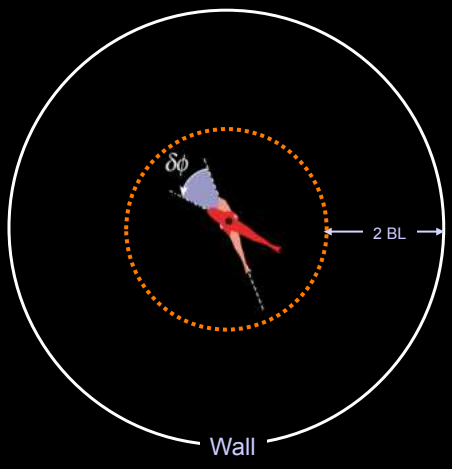
Calovi, D.S. *et al., PloS Comp. Biol.* (2018)

Analysis of individual swimming behavior

Spontaneous heading changes (away from the wall)

Distribution of angle change when the fish is far from the wall



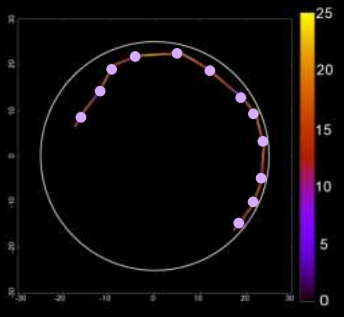


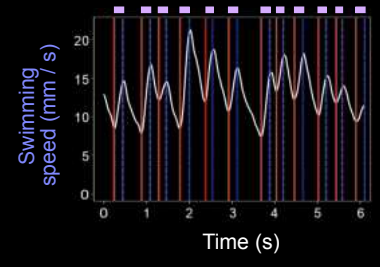
- The distribution of angle changes when the fish is far from the wall is almost Gaussian

Calovi, D.S. *et al., PloS Comp. Biol.* (2018)

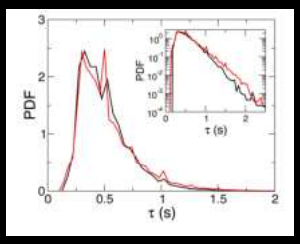
Analysis of individual swimming behavior

Duration and distance traveled by a fish between two kicks

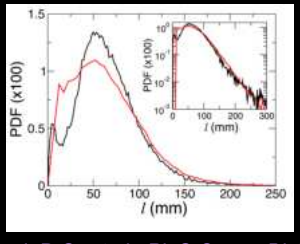




Duration between two kicks



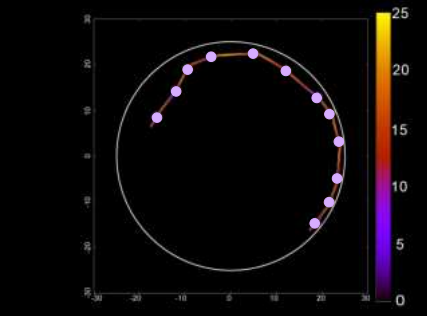
Distance travelled between two kicks

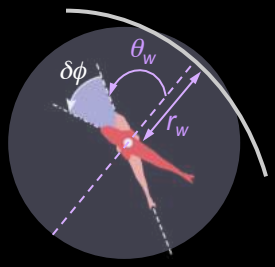


Calovi, D.S. *et al., PloS Comp. Biol.* (2018)

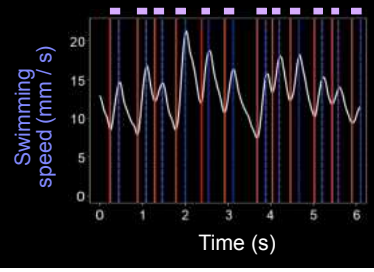
Measuring and modeling fish interaction with the wall

Reconstructing the stimulus-response functions





Reaction of fish to the wall



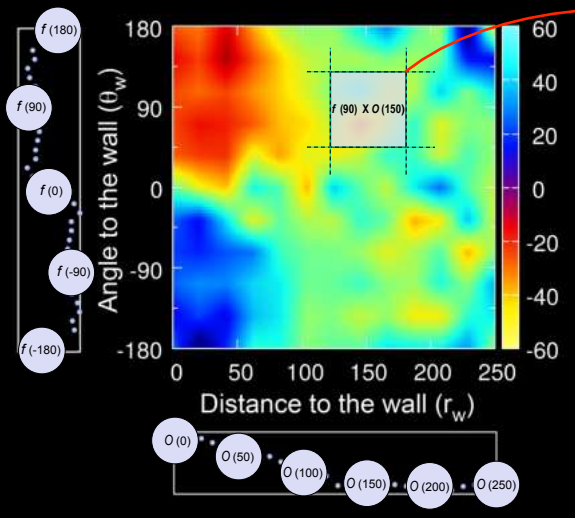
$$\delta\phi_{\mathrm{w}}(r_{\mathrm{w}},\theta_{\mathrm{w}}) = f(r_{\mathrm{w}})\, g(\theta_{\mathrm{w}})$$

- The heading variations of a fish result from the product of two decoupled functions of θ_w et r_w

Escobedo, R. *et al., Phil. Trans. R. Soc. B* (2020)

Measuring and modeling fish interaction with the wall

Reconstructing the stimulus-response functions



Average empirical angle change

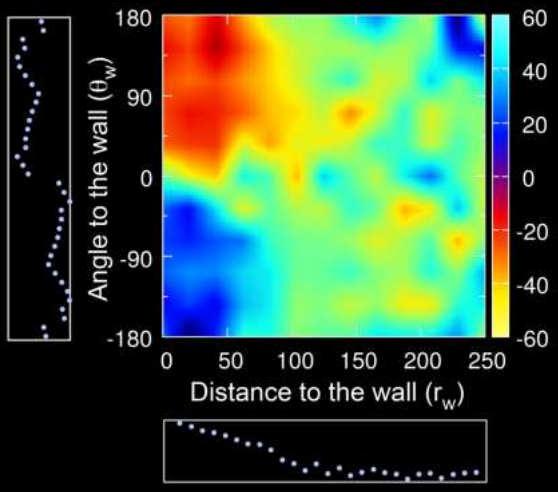
$$\Delta = \sum_{n=1}^{\#\,\mathrm{data}} [\delta\phi_n - f_{\mathrm{w}}(r_{\mathrm{w},n}) O_{\mathrm{w}}(\theta_{\mathrm{w},n})]^2$$

Find f_w and O_w that minimize Δ

Escobedo, R. *et al., Phil. Trans. R. Soc. B* (2020)

Measuring and modeling fish interaction with the wall

Reconstructing the stimulus-response functions

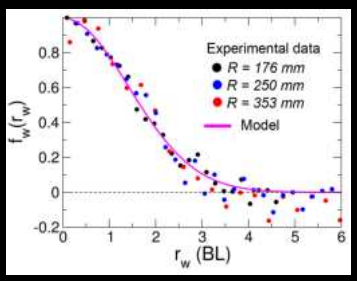


Escobedo, R. *et al., Phil. Trans. R. Soc. B* (2020)

Measuring and modeling fish interaction with the wall

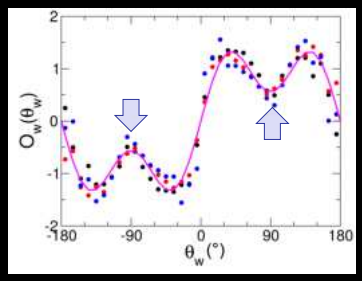
Extraction of interactions functions from trajectory data

Reaction of fish as a function of the distance to the wall



$$f_w(r_w) \propto \exp[-(r_w / l_w)^2]$$
$$l_w \approx 2\,\mathrm{BL} \sim 60\,\mathrm{mm}$$

Reaction of fish as a function of its relative orientation to the wall



$$O_w(\theta_w) \propto \sin\theta_w[1+\epsilon_2\cos 2\theta_w]$$
$$\epsilon_2 \approx 0.7$$

Calovi, D.S. *et al., PloS Comput. Biol.* (2018)

Modeling fish behavior and wall avoidance

Model description

- **1.** Fish randomly select an initial velocity and gliding time from the experimental distribution and define

$$l = v\tau_0\left[1-\exp\left(-\tau/\tau_0\right)\right] \quad (\tau_0 \approx 0.7s)$$

- **2.** Change the direction of the fish by an angle $\delta\phi$ with

$$\delta\phi = \delta\phi_R + \delta\phi_w$$

- **3.** Move over a distance of length l in the new direction
- **4.** Accept the move if the fish is still in the tank
- **5.** If not redraw $\delta\phi_R, v, \tau$

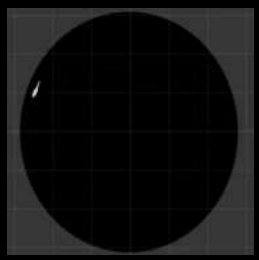
Calovi, D.S. *et al.*, *PloS Comput. Biol.* (2018)

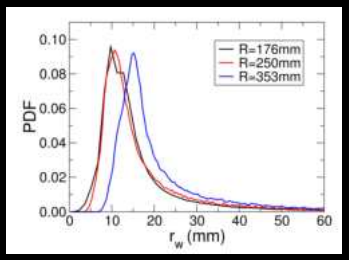
Simulations of the model

Spatial distribution and motion of a fish swimming alone

Distances of fish to the wall

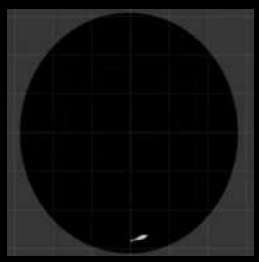
Experiment

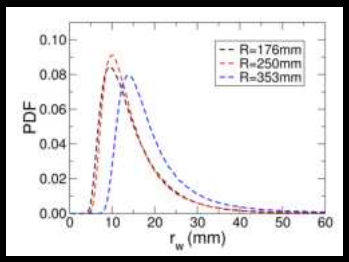




30 experiments (3.10^5 kicks)

Model





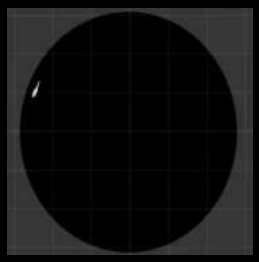
100 simulations (10^6 kicks each)

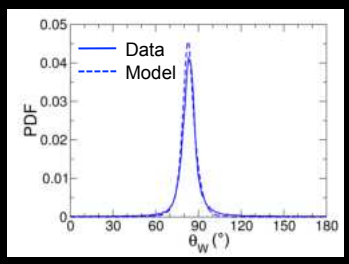
Calovi, D.S. *et al.*, *PloS Comput. Biol.* (2018)

Simulations of the model

Spatial distribution and motion of a fish swimming alone

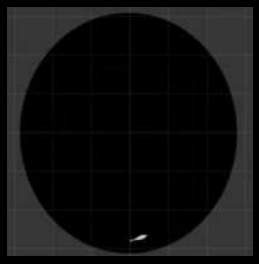
Experiment

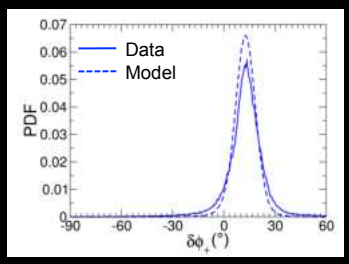




Relative orientation of the fish to the wall

Model





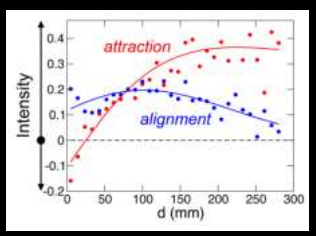
Heading changes of fish in the 353 mm diameter arena

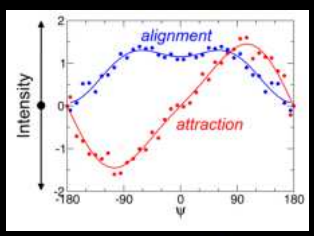
Calovi, D.S. *et al., PloS Comput. Biol.* (2018)

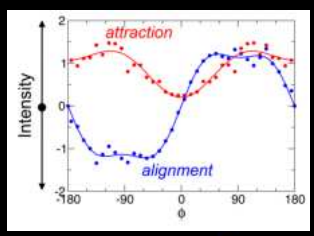
Measuring and modeling social interactions

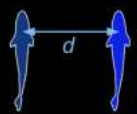
Attraction and alignment between two fish

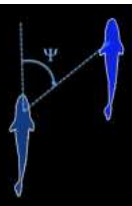
Distance *Angular position* *Relative heading*









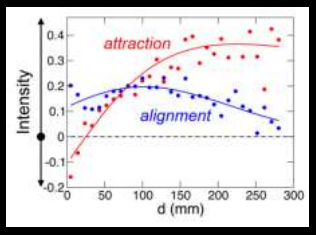


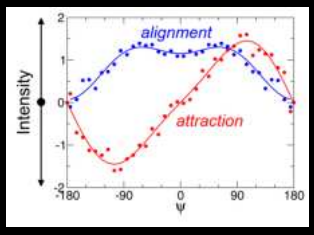
Calovi, D.S. *et al., PloS Comput. Biol.* (2018)

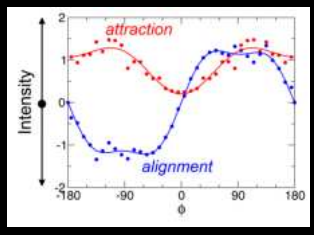
Measuring and modeling social interactions

Modeling the interactions between two fish

Distance | *Angular position* | *Relative heading*







$$F_{\mathrm{Att}}(d) \propto \frac{(d-a)/l_{\mathrm{Att}}}{1+(d/l_{\mathrm{Att}})^2}$$

$$O_{\mathrm{Att}}(\psi) \propto \sin(\psi)[1-0.33\cos(\psi)]$$

$$E_{\mathrm{Att}}(\Delta\phi) \propto 1+0.48\cos(\Delta\phi)-0.31\cos(2\Delta\phi)$$

$$F_{\mathrm{Ali}}(d) \propto \left(\frac{d}{l_{\mathrm{Ali}}}+c\right)\exp[-(d/l_{\mathrm{Ali}})^2]$$

$$E_{\mathrm{Ali}}(\psi) \propto 1+0.60\cos(\psi)-0.32\cos(2\psi)$$

$$O_{\mathrm{Ali}}(\Delta\phi) \propto \sin(\Delta\phi)[1+0.30\cos(2\Delta\phi)]$$

Calovi, D.S. *et al.*, *PloS Comput. Biol.* (2018)

Measuring and modeling social interactions

Modeling the interactions between two fish

- In the presence of another fish, the total heading angle change is the sum of the variations induced by the environment of the focal fish

$$\delta\phi = \delta\phi_{\mathrm{R}}(r_{\mathrm{w}}) + \delta\phi_{\mathrm{W}}(r_{\mathrm{w}},\theta_{\mathrm{w}}) + \delta\phi_{\mathrm{Att}}(d,\psi,\Delta\phi) + \delta\phi_{\mathrm{Ali}}(d,\psi,\Delta\phi)$$

- The angle change due to the social interactions is expressed in terms of decoupled functions of the instantaneous state of the fish: the distance (d), relative orientation (ψ) and alignment (ϕ) with its neighbor

$$\delta\phi_{\mathrm{Att}}(d,\psi,\Delta\phi) = F_{\mathrm{Att}}(d)O_{\mathrm{Att}}(\psi)E_{\mathrm{Att}}(\Delta\phi)$$

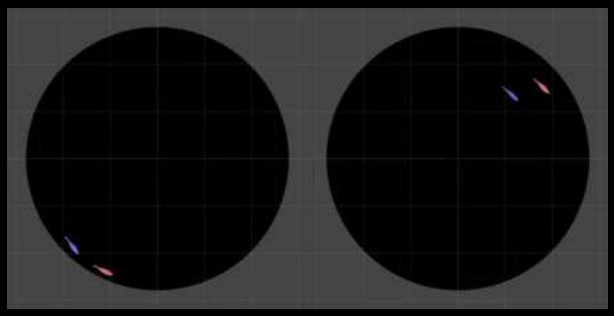
$$\delta\phi_{\mathrm{Ali}}(d,\psi,\Delta\phi) = F_{\mathrm{Ali}}(d)O_{\mathrm{Ali}}(\Delta\phi)E_{\mathrm{Ali}}(\psi)$$

Calovi, D.S. *et al.*, *PloS Comput. Biol.* (2018)

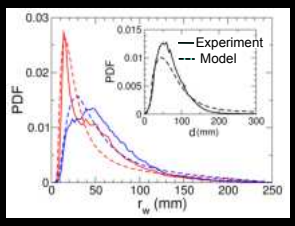
Modeling interactions between pairs of fish

Comparison between experiments and simulations

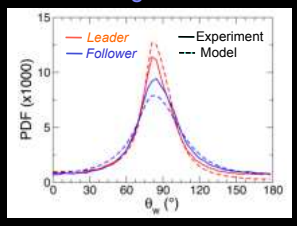
Experiment Model



Distance of fish to the wall and distance between fish



Relative angle to the wall

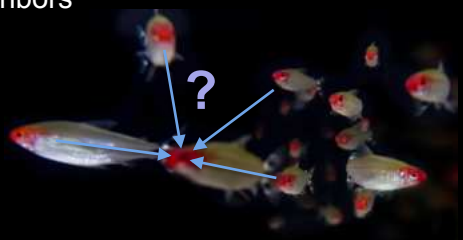


- The model qualitatively and quantitatively reproduces the key features of the motion and spatial distributions of fish observed in experiments

Calovi, D.S. *et al.*, *PloS Comput. Biol.* (2018)

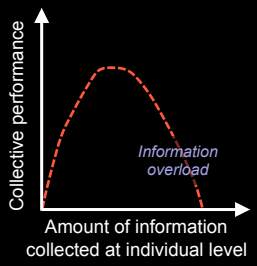
Combining interactions with multiple neighbors

Determining the influential neighbors



Hemigrammus rhodostomus

- How do fish combine the interactions with multiple neighbors when swimming in a school?
- What is the amount of information needed by fish about their environment to coordinate their motion?

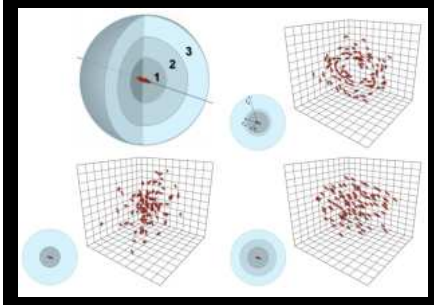


Lemasson, B.H., *J. Theor. Biol.* (2009)
Lei, L. *et al.*, *PloS Comput. Biol.* (2020)

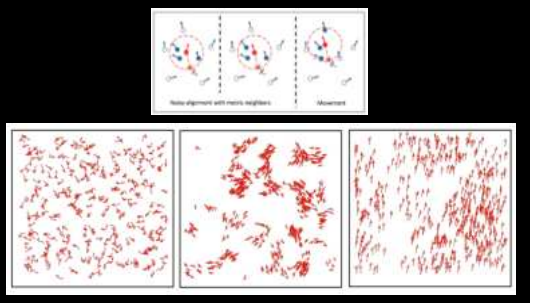
Combining interactions with multiple neighbors

Phenomenological models of schooling and flocking

Aoki-Couzin Model
Repulsion, orientation and attraction zones



Vicsek Model
Alignment interaction with neighbors inside a metric range R_0

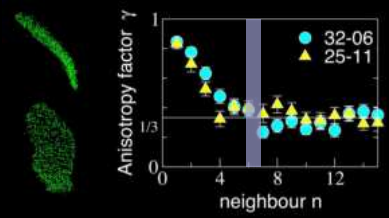


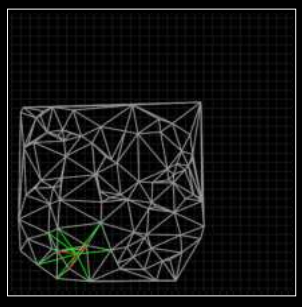
Aoki I. *Bull Japan Soc Sci Fish.* (1982)
Vicsek T. *et al. Phys. Rev. Lett.* (1995)
Couzin, I. *et al., J. theor. Biol.* (2002)

Combining interactions with multiple neighbors

Data-driven flocking and schooling models

Interaction ruling animal collective behavior depends on topological rather than metric distance: Evidence from a field study





- Each bird interacts on average with a fixed number of neighbors (6 – 7)

Ballerini, M. *et al., PNAS* (2008)
Gautrais, J. *et al., PloS Comput. Biol* (2012)

Combining interactions with multiple neighbors

The selective attention of fish to their neighbors

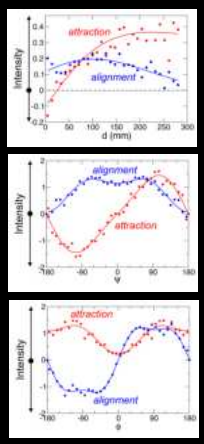
- To coordinate their movements rummy nose tetras only interact with the most or the two most influential neighbors
- These most influential neighbors are those fish that exert the strongest contribution to the heading variation of the focal fish

Jiang *et al., PloS Comput. Biol.* (2017)
Lei *et al., PloS Comput. Biol.* (2020)

Combining interactions with multiple neighbors

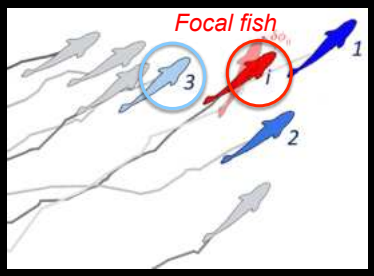
Identifying influential neighbors

Pairwise interaction functions



Ranking of neighbors according to their influence on a focal fish

$\delta\phi_{i1} > \delta\phi_{i2} > \delta\phi_{i3}$



- The influence exerted by one neighbor on a focal fish is calculated from the analytical expression of the pairwise interaction functions derived from experiments in groups of two fish

Jiang *et al., PloS Comput. Biol.* (2017)
Lei *et al., PloS Comput. Biol.* (2020)

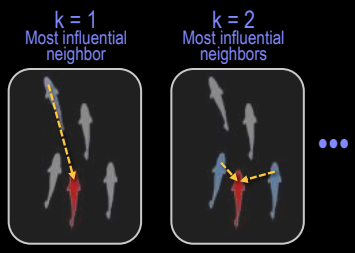
Combining interactions with multiple neighbors

Local interactions strategies

- Experiments with groups of 5 fish moving freely in a circular tank
- Testing different strategies for combining pairwise interactions between fish and analyze their impact on collective motion

$$\delta\phi_i^n = \delta\phi_{\mathrm{w},i}^n + \delta\phi_{\mathrm{R},i}^n + \sum_{j=1,j\neq i}^{N} \delta\phi_{ij}^n$$

Combination of pairwise interactions



Lei, L. *et al., PloS Comput. Biol.* (2020)

Combining interactions with multiple neighbors

Simulation results vs. experimental data when each fish interact with its k most influential neighbors

Group cohesion

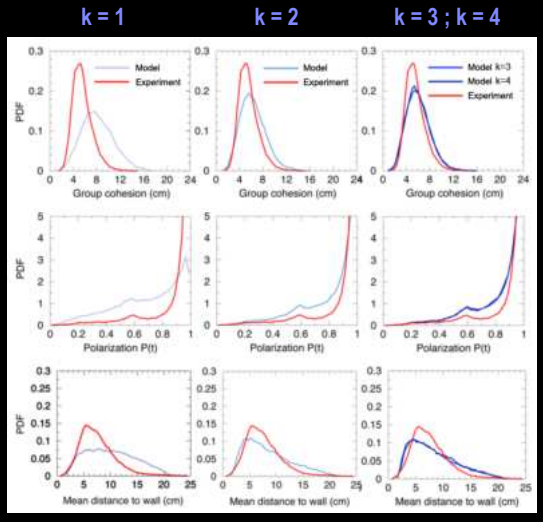
$$C(t) = \sqrt{\frac{1}{N}\sum_{i=1}^{N} \|\vec{u}_i - \vec{u}_B\|^2}$$

Group polarization

$$P(t) = \frac{1}{N}\left\|\sum_{i=1}^{N} \vec{e}_i(t)\right\|$$

Average distance of fish to the wall

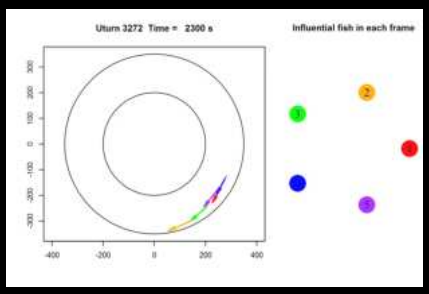
$$\langle r_w \rangle (t) = \frac{1}{N}\sum_{i=1}^{N} r_{w,i}(t)$$



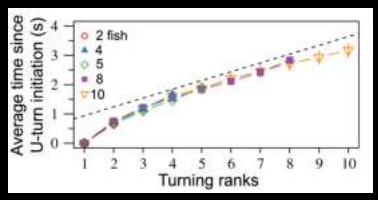
Lei, L. *et al., PloS Comput. Biol.* (2020)

Combining interactions with multiple neighbors

Dynamics of interactions between fish during collective U-turns



- During a collective U-turn, each fish copy the moving direction of one or two neighbors whose identity regularly changes
- The propagation of information is sequential, both in space and time (domino-like effect)



Jiang, L. *et al. PloS Comput. Biol.* (2017)
Lecheval, V. *et al., Proc. R. Soc. B* (2018)

Collective states in the fish school model

Impact of the intensity of the attraction and alignment interactions on collective states

Attraction intensity

$$F_{\mathrm{Att}}(d) = \gamma_{\mathrm{Att}} \frac{d/d_{\mathrm{Att}} - 1}{1 + (d/l_{\mathrm{Att}})^2}$$

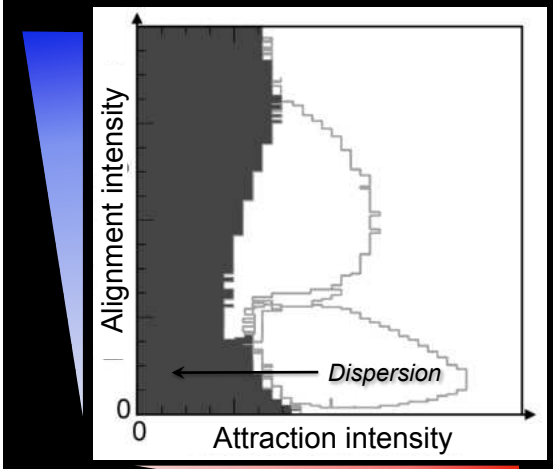
$$F_{\mathrm{Ali}}(d) = \gamma_{\mathrm{Ali}} \left(\frac{d}{d_{\mathrm{Ali}}} + 1 \right) \exp\left[-\left(\frac{d}{l_{\mathrm{Ali}}} \right)^2 \right]$$

Alignment intensity

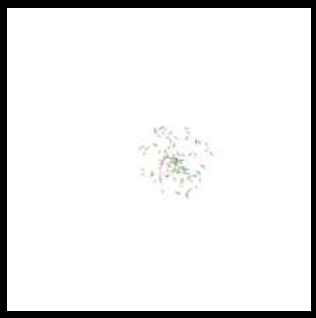
Wang, W. *et al., PloS Comp. Biol.* (2022)

Collective states in the fish school model

Impact of the intensity of the attraction and alignment interactions on collective states



Collective movement in a school of 100 fish

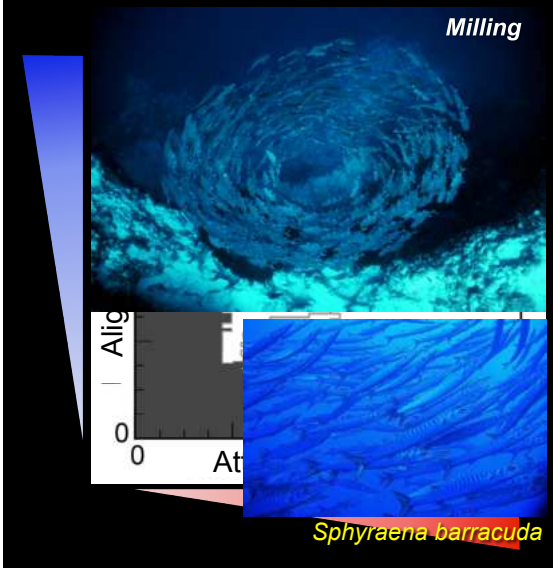


Each fish interacts with its most influential neighbor

Wang, W. *et al.*, *PloS Comp. Biol.* (2022)

Collective states in the fish school model

Impact of the intensity of the attraction and alignment interactions on collective states



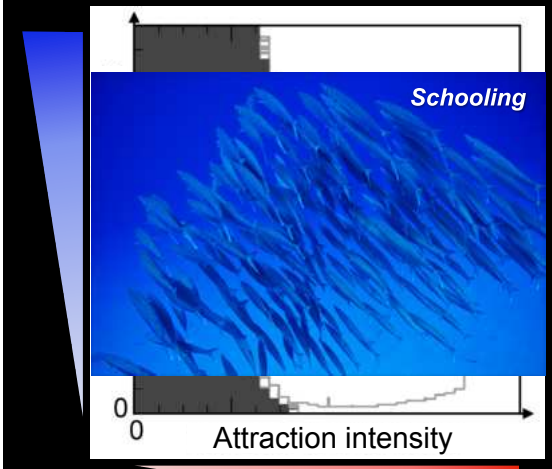
Collective movement in a school of 100 fish

Each fish interacts with its most influential neighbor

Wang, W. *et al.*, *PloS Comp. Biol.* (2022)

Collective states in the fish school model

Impact of the intensity of the attraction and alignment interactions on collective states



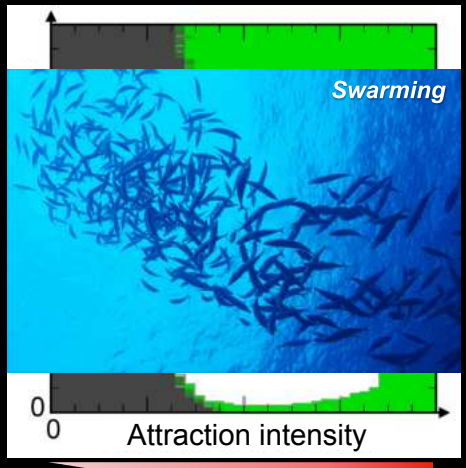
Collective movement in a school of 100 fish

Each fish interacts with its most influential neighbor

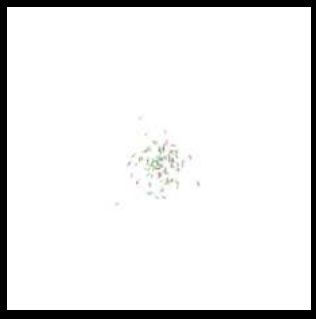
Wang, W. *et al., PloS Comp. Biol.* (2022)

Collective states in the fish school model

Impact of the intensity of the attraction and alignment interactions on collective states



Collective movement in a school of 100 fish

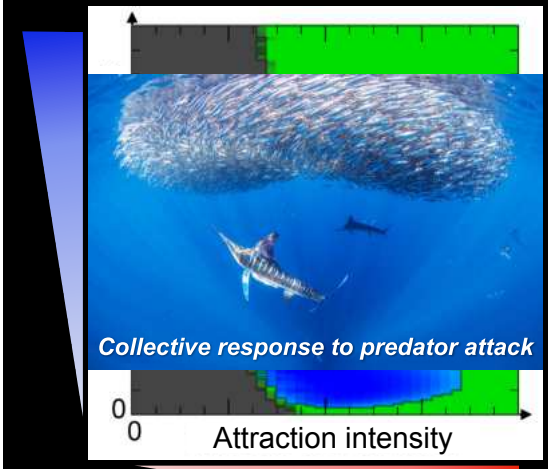


Each fish interacts with its most influential neighbor

Wang, W. *et al., PloS Comp. Biol.* (2022)

Collective states in the fish school model

Impact of the intensity of the attraction and alignment interactions on collective states



Collective movement in a school of 100 fish

Each fish interacts with its most influential neighbor

Calovi, D.S. *et al. J. R. Soc. Interface* (2015)
Wang, W. *et al., PloS Comp. Biol.* (2022)

Collective motion in groups of organisms

Criticality in swarms, schools, flocks and herds

- In many species, the interactions between individuals lead the group to a state that is neither too disorderly nor too rigidly organized, while being endowed with extreme sensitivity
- Being in a critical state enhances the collective adaptive capacity of a group

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© Walerian Walawski

© Christopher Swann

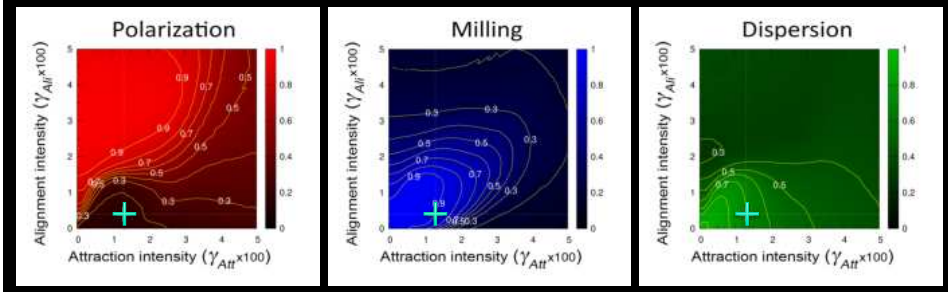
© Tim Whittaker

Attanasi, A . et al., *PloS Comp. Biol.* (2014); Bialek, W. *et al., PNAS* (2014) Calovi, D. *et al., J. R. Soc. Interface* (2015); Ginelli *et al., PNAS* (2015); Gómez-Nava; L. *et al., Nature Physics* (2023)

Collective states of fish schools in control condition

Estimation of the intensity of attraction and alignment interactions in groups of 25 fish without external disturbances

\+ Experimental data (25 lux)



- In controlled conditions, when fish are quiet, the school adopts a milling state

Group polarization

$$P(t) = \frac{1}{N}\left\|\sum_{i=1}^{N}\vec{e}_i(t)\right\|$$

Milling index

$$M(t) = \left|\frac{1}{N}\sum_{i=1}^{N}\sin(\vec{\theta}_w^{\perp}(t))\right|$$

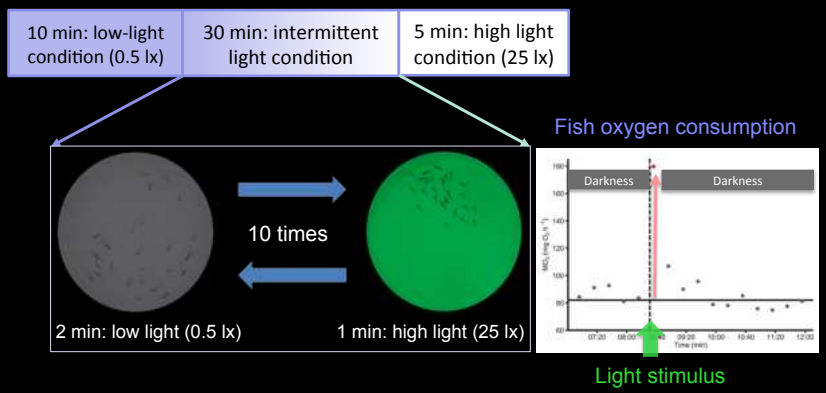
Group dispersion

$$D(t) = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\|\vec{u}_i - \vec{u}_B\|^2}$$

Lin, G. *et al.*, (*in prep.*)

Collective states of fish schools in intermittent light condition

Experimental protocol for inducing stress in fish

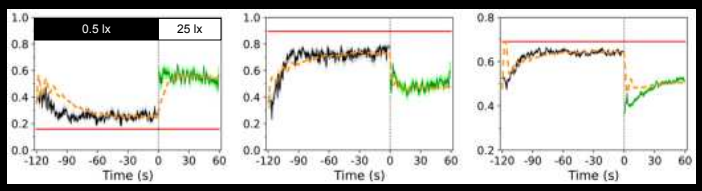


Aimon, C. *et al.*, *Sci. Total Environ.* (2022)
Lin, G. *et al.*, (*in prep.*)

Collective states of fish schools in intermittent light condition

Effect of intermittent light on collective response in groups of 25 fish

Group polarization | Milling index | Group dispersion

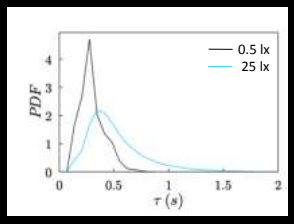


Lin, G. *et al.*, (*in prep.*)

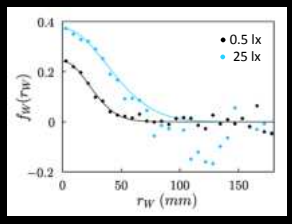
Collective states of fish schools in intermittent light condition

Effect of intermittent light on individual fish response

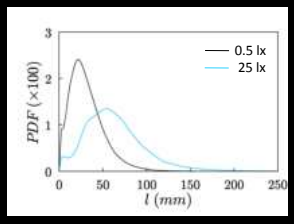
Duration between two kicks



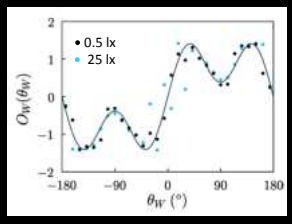
Reaction of fish as a function of the distance to the wall



Distance travelled between two kicks



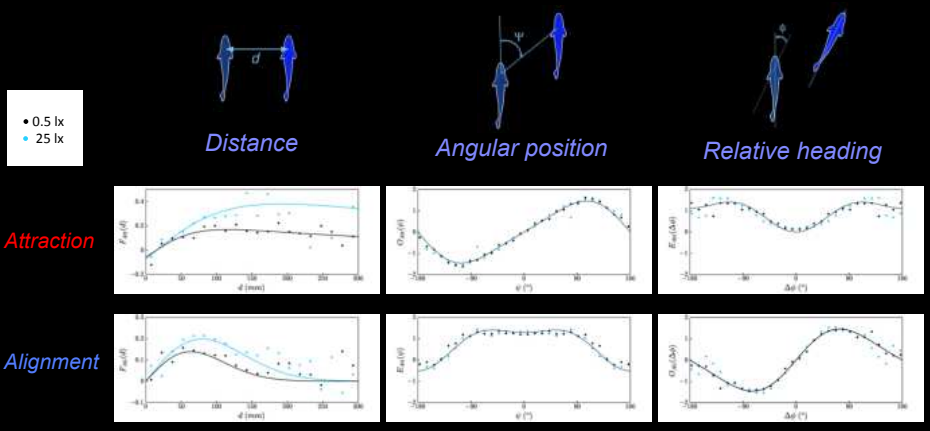
Reaction of fish as a function of its relative orientation to the wall



Xue, T. *et al.*, *PloS Comp. Biol.* (2023)
Lin, G. *et al.*, (*in prep.*)

Collective states of fish schools in intermittent light condition

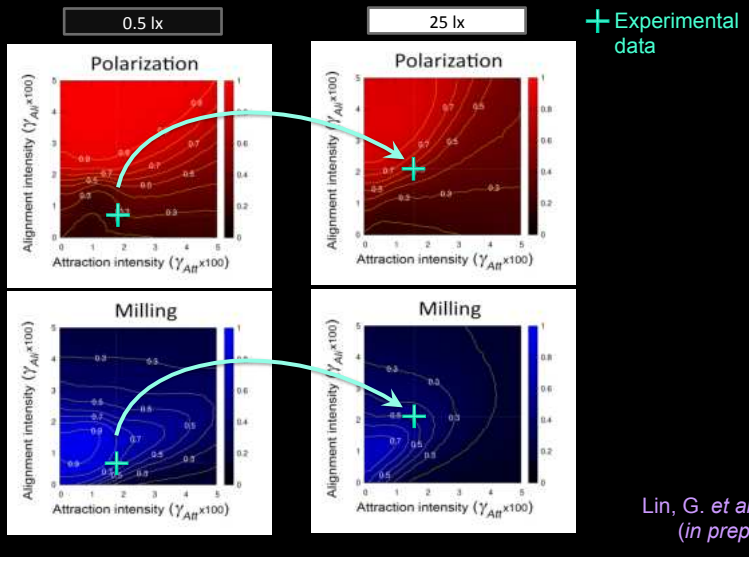
Effect of intermittent light on Individual fish response



Xue, T. *et al., PloS Comp. Biol.* (2023)
Lin, G. *et al., (in prep.)*

Collective states of fish schools in intermittent light condition

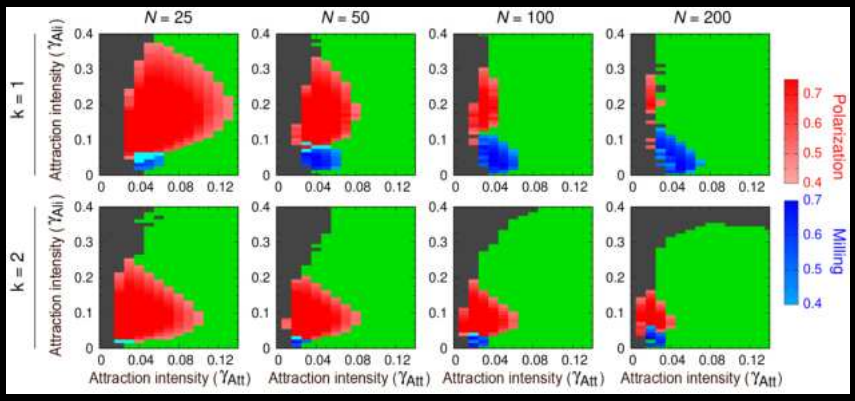
Estimation of the intensity of attraction and alignment interactions in groups of 25 fish in stressed conditions



Lin, G. *et al., (in prep.)*

Collective states in the fish school model

Impact of group size on collective states



- As group size increases, the schooling phase shrinks and is replaced by the swarming state
- The maximum group size reported for *Hemigrammus rhodostomus* rarely exceeds 30

Böhlke, J., *Trans. Kans. Acad. Sci.* (1955)
Wang, W. *et al., PloS Comp. Biol.* (2022)

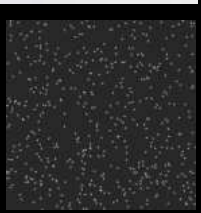
Investigating schooling behavior with swarm robotics

Introducing the "Cuboids"

Liu Lei

- A swarm robotic platform to investigate flocking behavior and the integration of information at individual scale

Craig Renolds

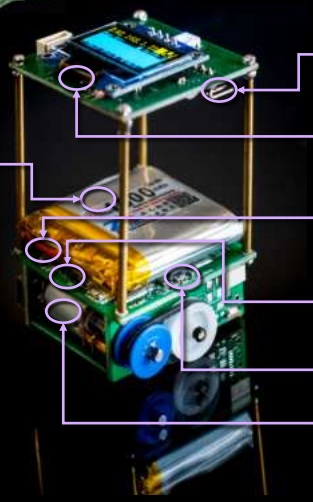


"Boids" simulation

Reynolds, C.W., *ACM SIGGRAPH Computer Graphics* (1987)

Investigating schooling behavior with swarm robotics

Hardware and interfaces of the “Cuboid” mobile robot



1800 mAh Li-Pily battery

IR short-range sensing and communication system

Motion Tracking device sensor MPU-9250

8-bit microcontroller PIC18F25k22

32-bit, 168 MHz ARM microprocessor STM32F4

IEEE 802.11n / WIFI module

3.7 v DC motors (52 ± 4mm/s)

Lei, L. *et al.*, *PloS Comput. Biol.* (2020)

Investigating schooling behavior with swarm robotics

The “Cuboids” robots platform

Wireless router

Computer

Image processing system

- Image acquisition
- Pattern matching
- Data conversion

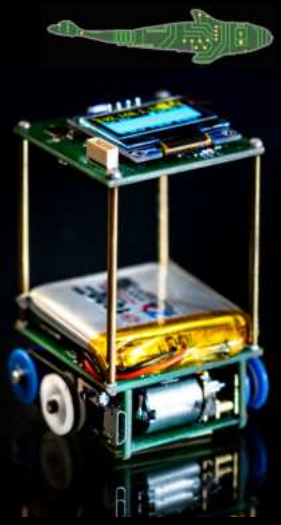
Robots distributed loop cycle (20ms)

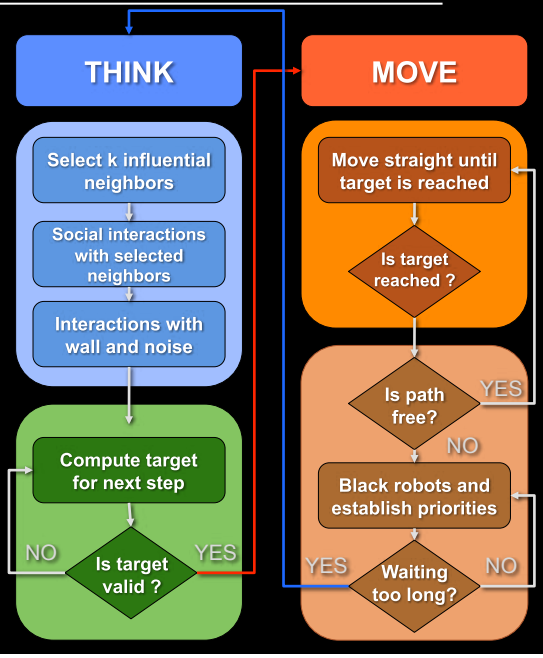
- Robot ID tracker
- Robot location information
- Object oriented programming software for robots distributed control
  - Single robot running state machine (place target decision strategy)
- Cuboids robot actuators wireless control system

Lei, L. *et al.*, *PloS Comput. Biol.* (2020)

Investigating schooling behavior with swarm robotics

Behavioral model





Lei, L. *et al., PloS Comput. Biol.* (2020)

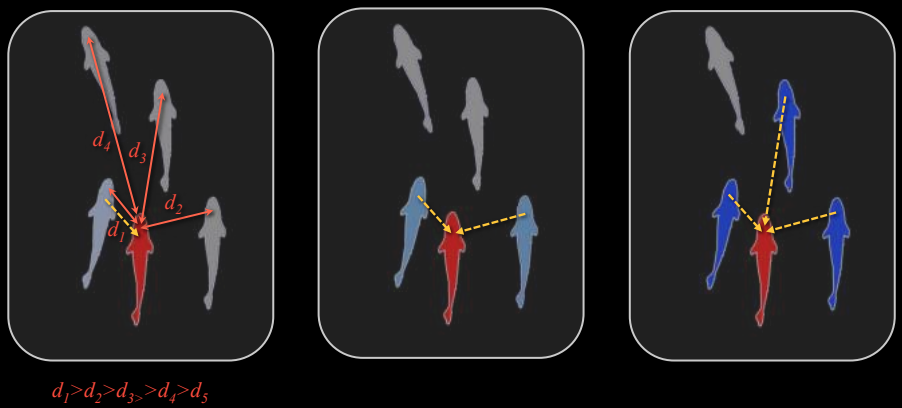
Interaction strategies

Interacting with the *k* NEAREST neighbors

Interaction with the first nearest neighbor

Interaction with the two first nearest neighbors

Interaction with the three first nearest neighbors



$d_1 > d_2 > d_3 > d_4 > d_5$

Lei, L. *et al., PloS Comput. Biol.* (2020)

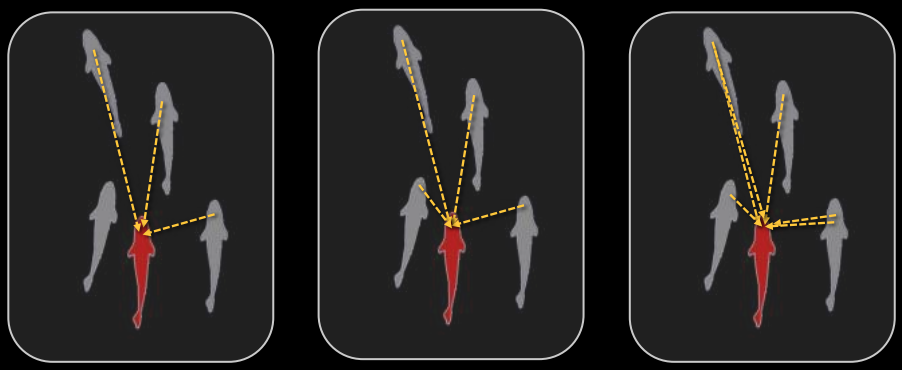
Interaction strategies

Interacting with the *k* RANDOMLY chosen neighbors

Interaction with 1 randomly chosen neighbor

Interaction with 2 randomly chosen neighbors

Interaction with 3 randomly chosen neighbors



Lei, L. *et al.*, *PloS Comput. Biol.* (2020)

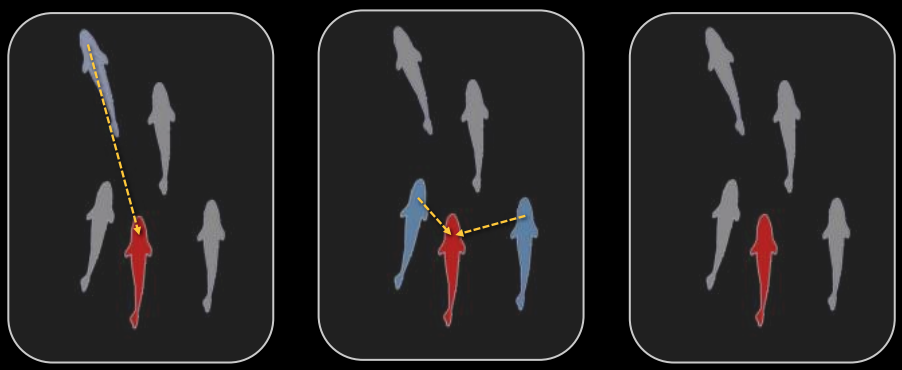
Interaction strategies

Interacting with the *k* MOST INFLUENTIAL neighbors

Interaction with the most influential neighbor

Interaction with the 2 most influential neighbors

No interaction (null model)



- The influence $I_{ij}(t)$ of a neighbor j on a focal individual i at time t is is calculated by means of the analytical expressions of the pairwise interaction functions between fish swimming in pairs

Lei, L. *et al.*, *PloS Comput. Biol.* (2020)

Integrating interactions with multiple neighbors

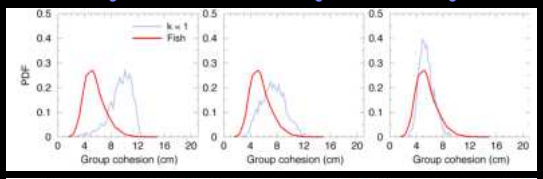
Swarm robotics experiments vs fish experiments with k = 1

Scaling factor
λ_R: 0.35

NEAREST neighbor | RANDOMLY chosen neighbor | MOST INFLUENTIAL neighbor

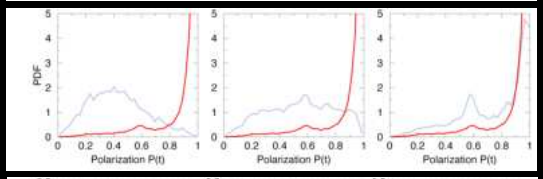
Group cohesion

$$C(t) = \sqrt{\frac{1}{N}\sum_{i=1}^{N} \|\vec{u}_i - \vec{u}_B\|^2}$$



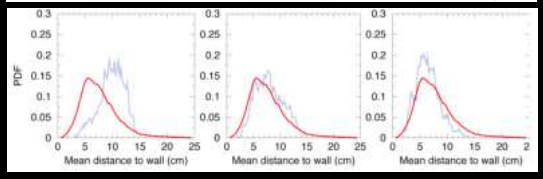
Group polarization

$$P(t) = \frac{1}{N}\left\|\sum_{i=1}^{N} \vec{e}_i(t)\right\|$$



Distance of the barycenter to the wall

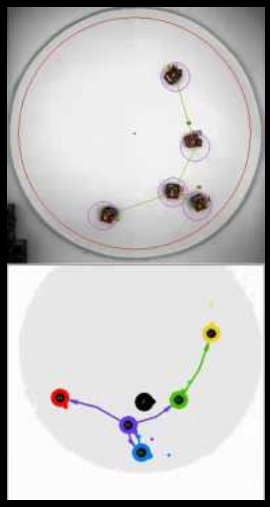
$$r_w^B(t) = R - \sqrt{(x_B(t))^2 + (y_B(t))^2}$$

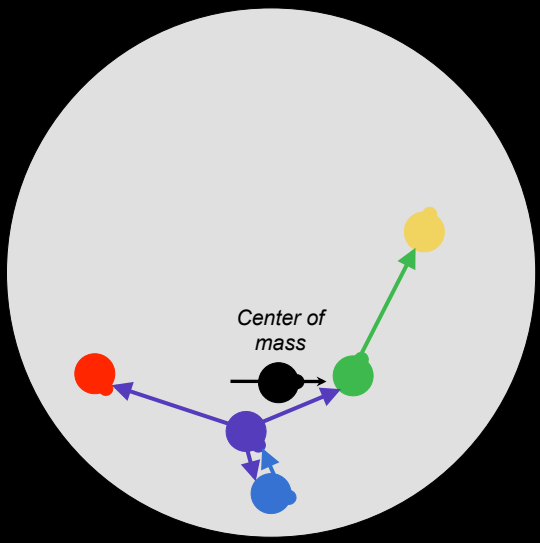


Results of the robotic experiments

k = 1

Interaction with the NEAREST neighbor





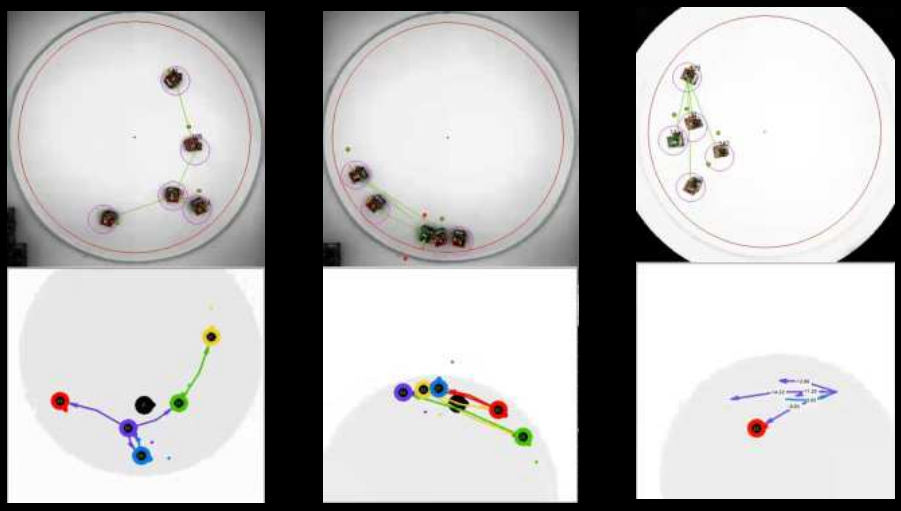
Results of the robotic experiments

k = 1

Interaction with the NEAREST neighbor

Interaction with a RANDOMLY chosen neighbor

Interaction with the MOST INFLUENTIAL neighbor



Integrating interactions with multiple neighbors

Swarm robotics experiments vs fish experiments with k = 2

Scaling factor λ_R*: 0.35*

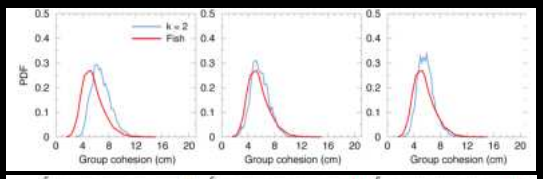
NEAREST neighbor

RANDOMLY chosen neighbor

MOST INFLUENTIAL neighbor

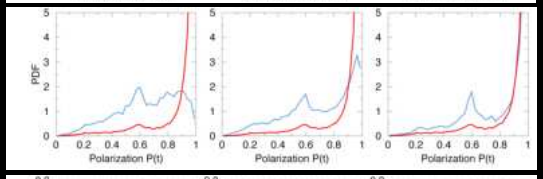
Group cohesion

$$C(t) = \sqrt{\frac{1}{N}\sum_{i=1}^{N} \|\vec{u}_i - \vec{u}_B\|^2}$$



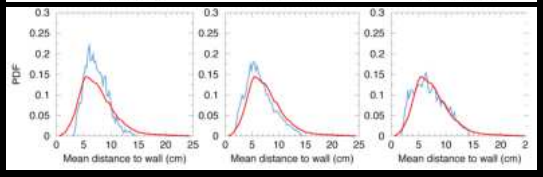
Group polarization

$$P(t) = \frac{1}{N}\left\|\sum_{i=1}^{N} \vec{e}_i(t)\right\|$$



Distance of the barycenter to the wall

$$r_w^B(t) = R - \sqrt{(x_B(t))^2 + (y_B(t))^2}$$



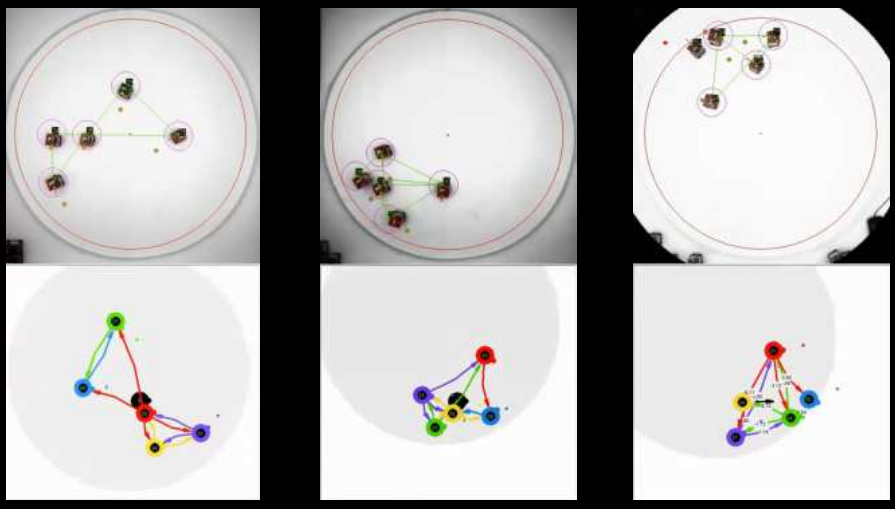
Results of the robotic experiments

k = 2

Interaction with the 2 NEAREST neighbors

Interaction with 2 RANDOMLY chosen neighbors

Interaction with the 2 MOST INFLUENTIAL neighbors



Integrating interactions with multiple neighbors

Swarm robotics experiments vs fish experiments with k = 3, 4

Scaling factor λ_R: *0.35*

NEAREST neighbor

RANDOMLY chosen neighbor

MOST INFLUENTIAL neighbor

Group cohesion

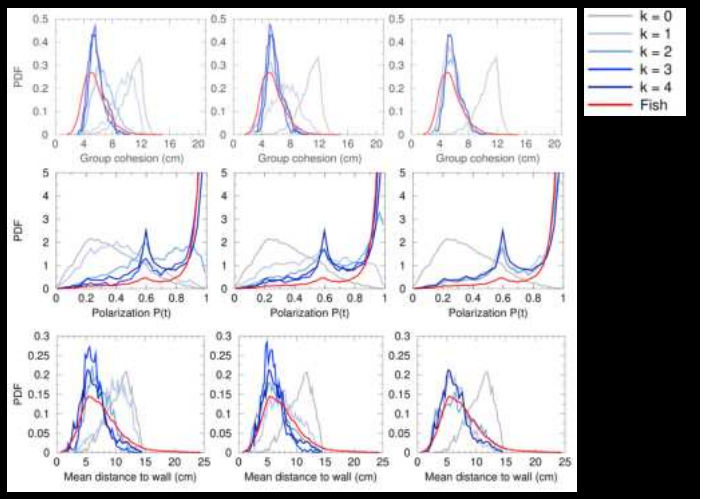
$$C(t) = \sqrt{\frac{1}{N}\sum_{i=1}^{N} \|\vec{u}_i - \vec{u}_B\|^2}$$

Group polarization

$$P(t) = \frac{1}{N}\left\|\sum_{i=1}^{N} \vec{e}_i(t)\right\|$$

Distance of the barycenter to the wall

$$r_w^B(t) = R - \sqrt{(x_B(t))^2 + (y_B(t))^2}$$



Coordination mechanisms in fish schools

Conclusions

- An incremental approach to build a fish behavior model completely based on interactions with the physical environment and neighboring fish
- A continuous balancing between attraction and alignment behavior as a function of the distance between fish and their relative positions and orientations

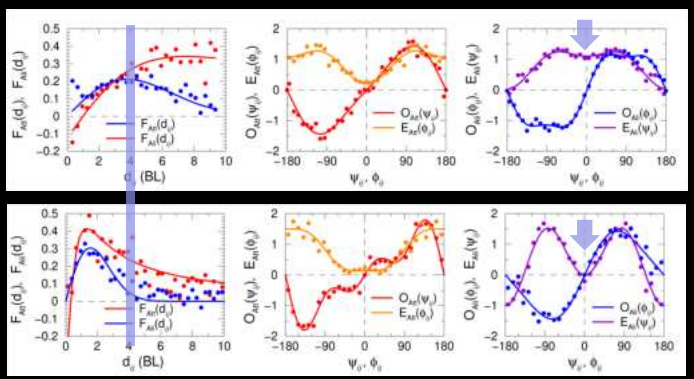
Hemigrammus rhodostomus

Calovi, D.S. *et al.*, *PloS Comput. Biol.* (2018)

Coordination mechanisms in fish schools

Comparison of social interactions in *H. rhodost*omus and *D. rerio*

Attraction *Alignment* | *Attraction* | *Alignment*



Hemigrammus rhodostomus

Dano rerio

Escobedo, R. *et al.*, *Phil. Trans. R. Soc. B* (2020)

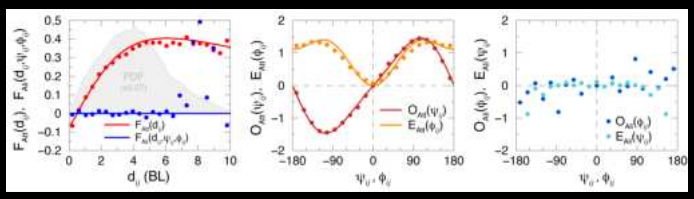
Coordination mechanisms in fish schools

Reconstructing interactions from simulation data without alignment

Attraction
Alignment

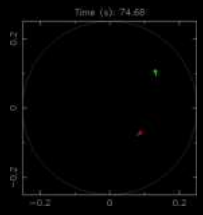
Attraction

Alignment

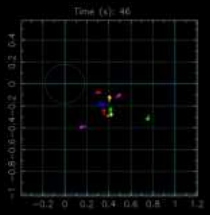


Couzinas dubium
(purely fictional species)

N=2 fish



N=10 fish



Each fish interacts with its two most influential neighbors

Coordination mechanisms in fish schools

Conclusions

- Each fish must acquire only a minimal amount of information about the behavior of its neighbors for coordination to emerge at the group level

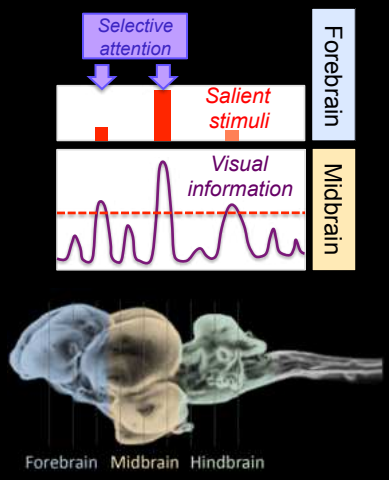
Hemigrammus rhodostomus

Jiang *et al., PloS Comput. Biol.* (2017)
Lei *et al., PloS Comput. Biol.* (2020)

Coordination mechanisms in fish schools

Conclusions

- Each fish must acquire only a minimal amount of information about the behavior of its neighbors for coordination to emerge at the group level
- In vertebrates the midbrain continuously monitors the environment for the relevant stimuli and the forebrain selects those stimuli on which the fish focuses its attention
- Fish do not have to pay attention to all their neighbors to ensure the coordination of swimming

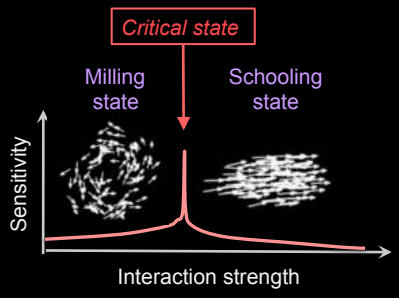


Lei, L. *et al., PloS Comput. Biol.* (2020)
Knudsen, E.I. *Trends Neurosci.* (2018)

Coordination mechanisms in fish schools

Conclusions

- In response to intermittent light conditions, the state of fish changes and moves into a specific region in the attraction-alignment phase space near the transition region between milling and schooling
- In this region the susceptibility, and hence the fluctuations of the polarization and milling order parameters is maximal
- As a consequence the state of the fish school becomes critical and the responsiveness of the school to perturbations is maximum

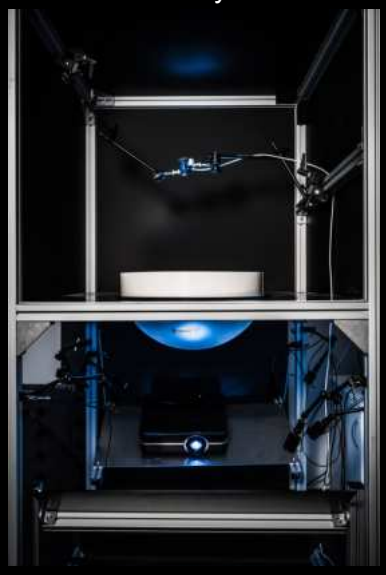


Lei, L. *et al., PloS Comput. Biol.* (2020)
Knudsen, E.I. *Trends Neurosci.* (2018)
Lin, G. *et al., (in prep.)*

Perspectives: Analyzing the interactions of a real fish with a virtual fish

A closed-loop feedback system based on virtual reality

- Model's predictions with two real fish swimming in the tank can be compared to the actual behavior of a real fish interacting with a virtual fish whose behavior is controlled in real-time by the model integrating the information collected on the behavior of the real fish

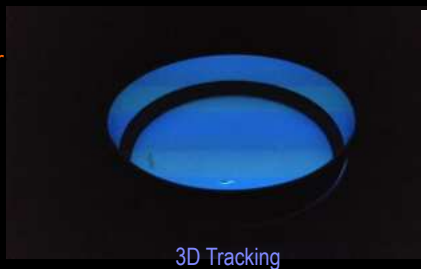


Perspectives: Analyzing the interactions of a real fish with a virtual fish

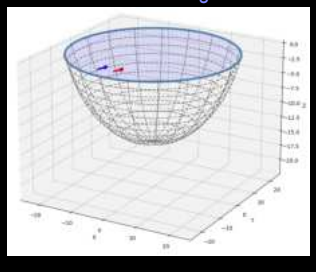
A closed-loop feedback system based on virtual reality

- The closed-loop virtual reality system allows for an in-depth analysis of the behavioral and cognitive processes involved in decision-making in a collective context
- The system makes it possible to study the visual information used by fish to control their movements and ultimately to validate the models

Interaction between a real and a virtual fish



3D Tracking



Real Fish
Virtual Fish