Maximizing swimming thrust of bio-inspired robotic fish using machine learning

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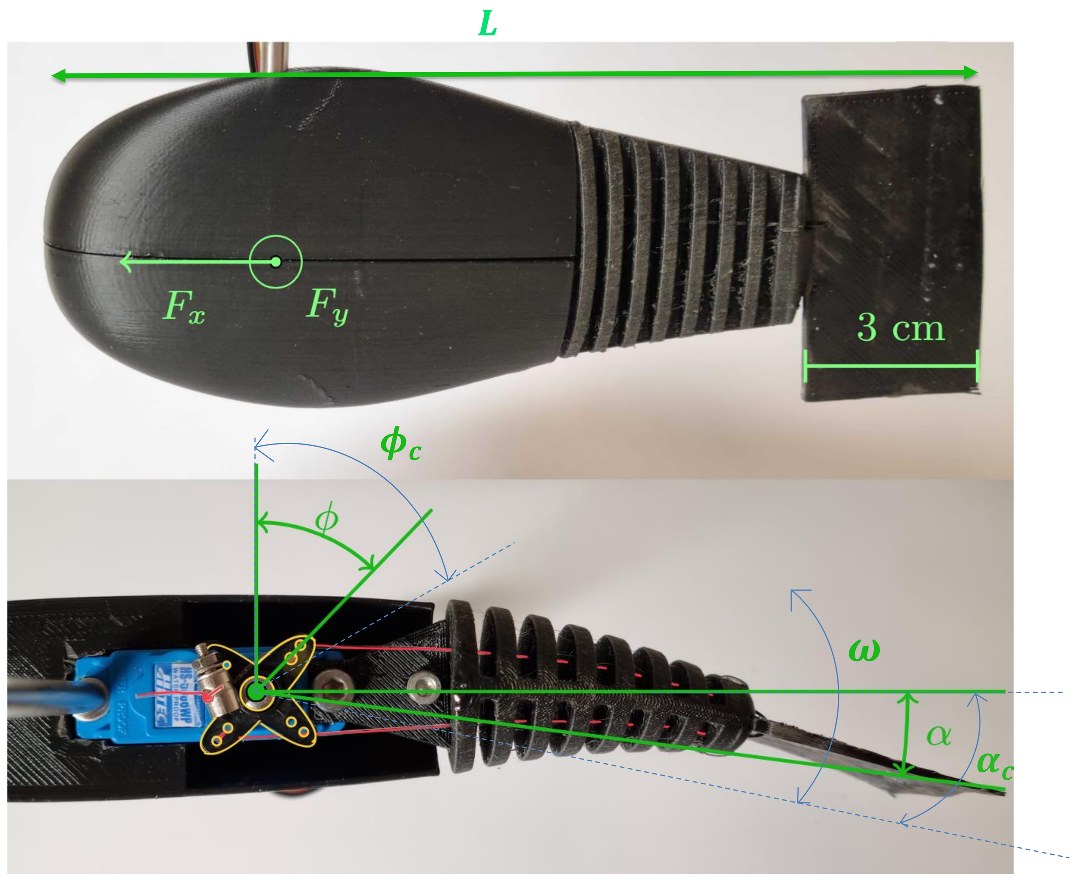
ABSTRACT

In the context of fish locomotion, the selection of swimming gait and the relationship between fish kinematics and swimming speed remain among the most fundamental and open questions at the same time. To address these questions, we employ deep reinforcement learning algorithms to maximize the thrust production of biomimetic robotic fish, utilizing various sensors. We also develop a simple model describing fish dynamics without any free parameter. By comparing the learning in simulation and experiment using different approaches, we find excellent agreement on the optimal gait, the frequency and amplitude of caudal fin oscillation. We propose an intuitive procedure for driving robotic fish in an optimal way. The best control consists in a square-wave function whose frequency can be selected with simple principles. We also study the speed optimization of fish both in simulation and in experiment.

BIO-INSPIRED ROBOTIC FISH MODEL



- Robotic fish of length $L \sim 10$ cm
- Undamped angular frequency of the oscillator $\omega_0 \sim 13$ rad.s^{-1}
- Damping coefficient $\xi \sim 1.2$
- Servomotor's maximum angular velocity $\Omega \sim 6$ rad.s^{-1}
- Coefficient of thrust efficiency $K \sim 1.29 \cdot 10^{-2}$ N.rad^{-2}.s^{2}
- Normalization constant $\Delta\phi \sim 0.29$ rad
- Maximum servo-motor's instruction angle Φ

Modeled as forced harmonic oscillator

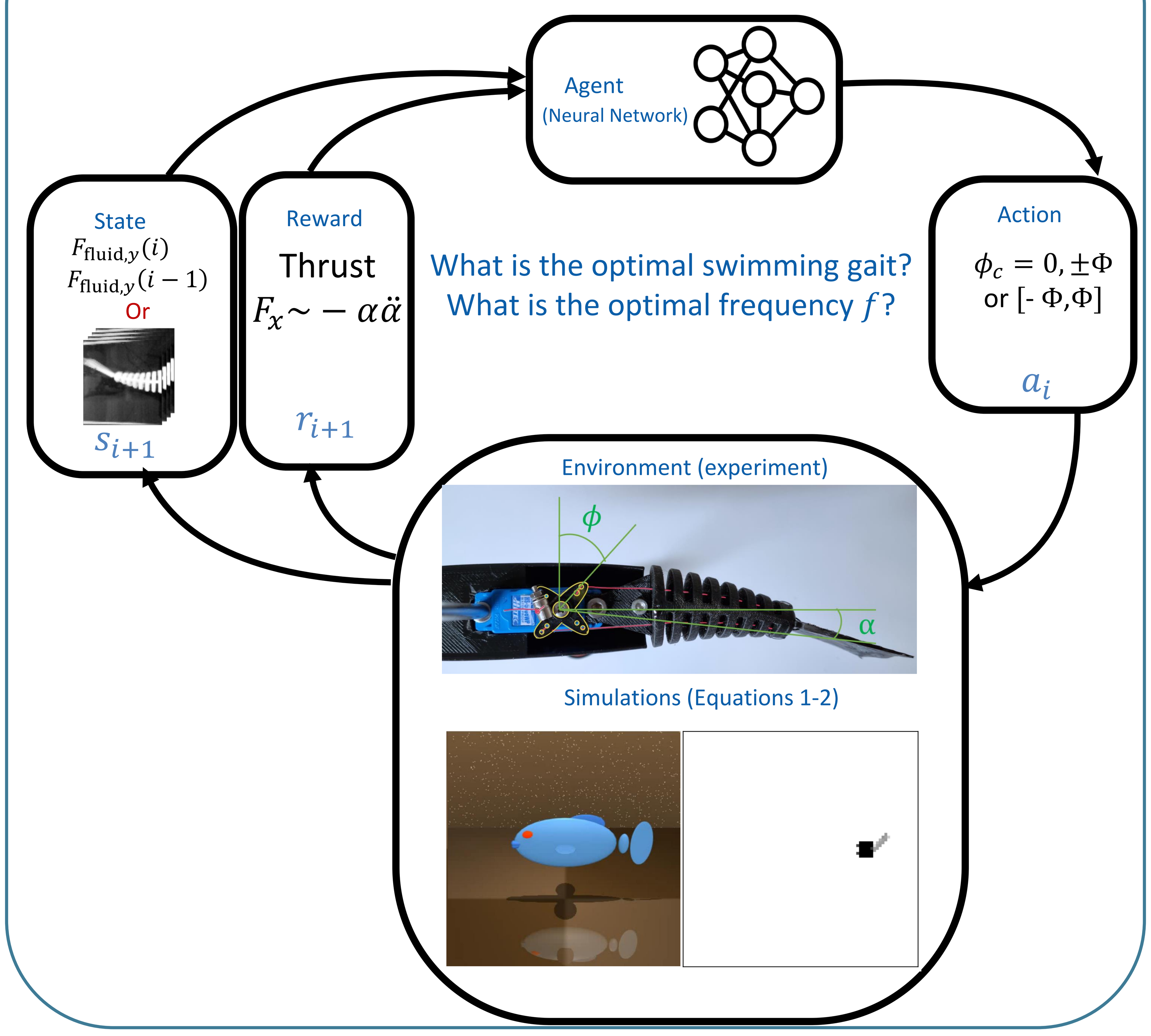
- Servomotor's instruction angle ϕ_c
- Servomotor's angle ϕ
- Fin instruction angle α_c
- Fin angle α
- Undulation period $T=2\pi/\omega$

$$(1)\ \ddot{\alpha} + \xi\omega_0\dot{\alpha} + \omega_0^2(\alpha - \alpha_c) = 0\,, \alpha_c = \lambda\phi_c$$

$$(2)\ \dot{\phi} = \Omega \tanh\left(\frac{1}{\Delta\phi}(\phi_c - \phi)\right)$$

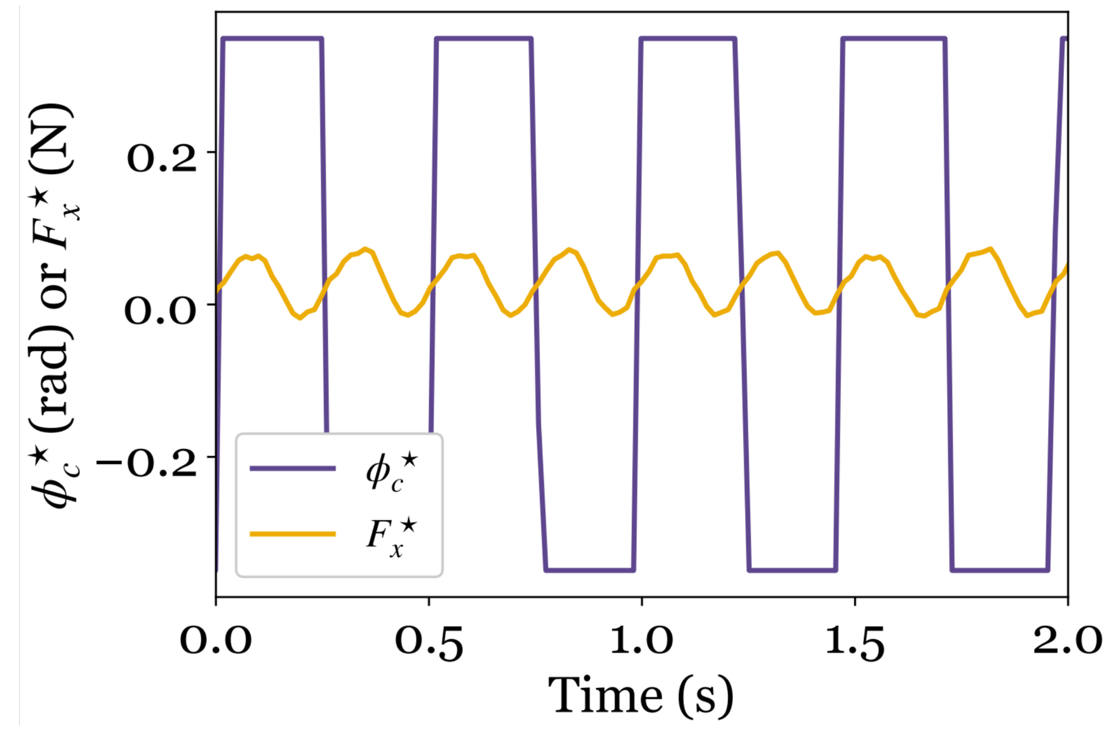
$$\overline{F_x} = -\frac{K}{T}\int_0^T \alpha\,\ddot{\alpha}\,dt$$

REINFORCEMENT LEARNING

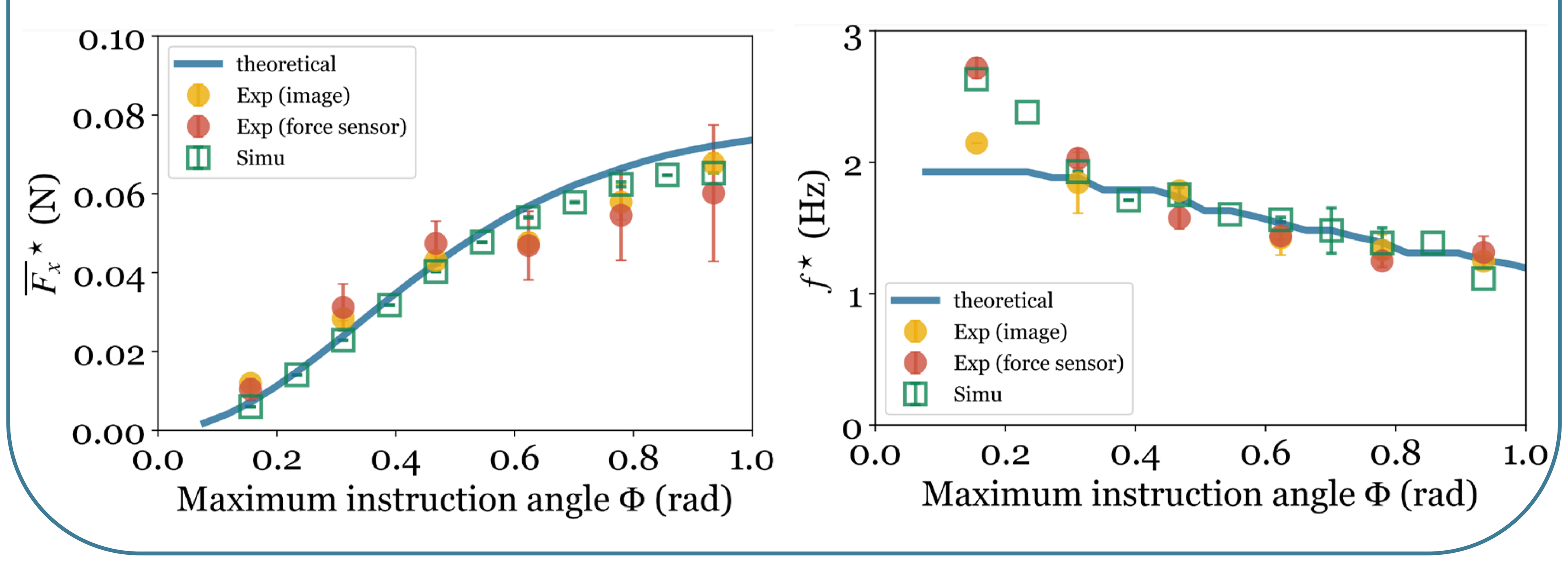


RESULTS

1. Optimal swimming gait for thrust maximization is a **square-wave**

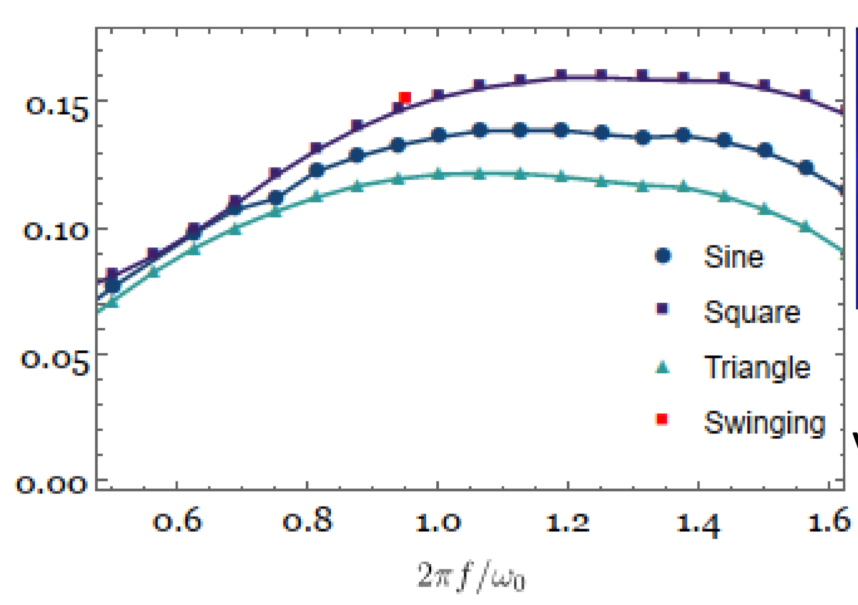


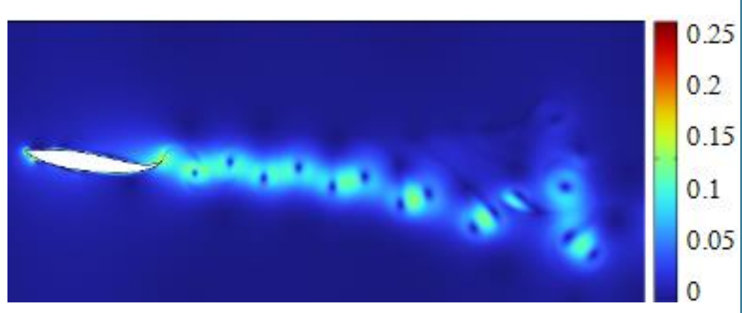
2. Experiment and Model comparison. Deep RL predict the optimal ω, α_c



SPEED MAXIMIZATION

COMSOL Multiphysics





2D numerical simulation validates "swinging" approach

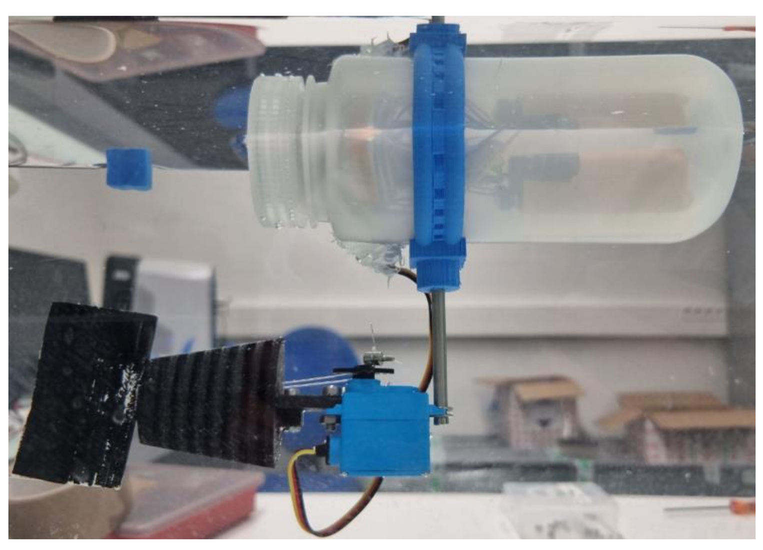
swinging strategy : $\phi_c = \pm\Phi$ when $\dot{\alpha} = 0, \ddot{\alpha} <> 0$

square-wave gait maximizes the speed

CONCLUSION

We have studied the interrelation of kinematics and thrust production of a bio-inspired robotic fish. We developed a simple model describing fish dynamics. We conducted thrust optimization with different approaches to confirm the optimal swimming gait, frequency and amplitude of fin oscillations. Our basic model allows for a manageable experiment and has demonstrated strong predictive abilities.

Next : learning to free swim



[1] Sánchez-Rodríguez, Celestini, Raufaste and Argentina, PRL, 2021.
[2] Gazzola, Argentina and Mahadevan, PNAS, 2015.
[3] Theodorsen, NACA, 1935.
[4] Sutton and Barto, Reinforcement Learning: An introduction, 2018.
[5] COMSOL Multiphysics® v. 6.1. www.comsol.com. COMSOL AB, Stockholm, Sweden.
[6] OpenAI Gym;. https://https://gym.openai.com/
[7] Tunyasuvunakool, Saran et al. "dm_control: Software and Tasks for Continuous Control." Software Impacts, vol. 6, 2020, p. 100022, doi: 10.1016/j.simpa.2020.100022.