

Information processing in soft robots II: Physical reservoir computing

Kohei Nakajima
University of Tokyo

2024/11/08 Friday, 16:20-17:50
立命館大学：特殊講義（ソフトロボット学）
zoom

Contents

1. 11/1: Reservoir computing

Nonlinear dynamics as computational device

2. 11/8: Physical reservoir computing

Soft body dynamics as computational device

The report topic will be announced at the final lecture (11/8)!

contents

1. Genesis of liquid state machine

2. Physical reservoir computing

Two representative models in RC

Echo state network

H. Jaeger, Tech. Rep. No. 148. Bremen: German National Research Center for Information Technology (2001).

H. Jaeger et al., Science, Vol.304. no.5667, pp.78–80 (2004).

Herbert Jaeger

- Randomly coupled network
- Artificial neural network (Sigmoidal function)
- Engineering oriented



* Similar architectures can be found at least in 1990.

Liquid state machine

W. Maass et al., Neural Comput 14 (11): 2531–60, 2002.

W. Maass, & H. Markram, H. Journal of computer and system sciences, 69(4), 593-616, 2004.

Wolfgang Maass

- Often assume space
- Pulse neuron
- Neuroscience oriented



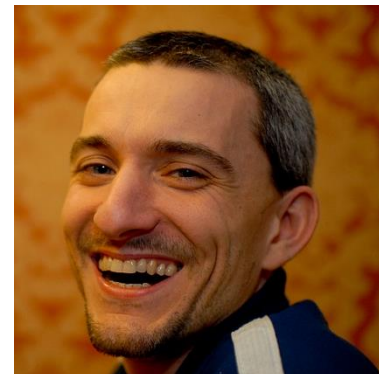
Early 2000

Conception in around 2005!

Let us unify the approach in the same umbrella!

Reservoir computing

Benjamin Schrauwen,
Joni Dambre
(University of Gent)



Genesis of liquid state machine
: wetware, liquid computer, liquid brain

Brain as a “wetware”

If you pour water over your PC, the PC will stop working. This is because very late in the history of computing – which started about 500 million years ago¹ – the PC and other devices for information processing were developed that require a dry environment. But these new devices, consisting of *hardware* and *software*, have a disadvantage: they do not work as well as the older and more common computational devices that are called *nervous systems*, or *brains*, and which consist of *wetware*. These superior computational devices were made to function in a somewhat salty aqueous solution, apparently because many of the first creatures with a nervous system were coming from the sea. We still carry

¹ One could also argue that the history of computing started somewhat earlier, even before there existed any nervous systems: 3 to 4 billion years ago when nature discovered information processing via RNA.

W. Maass. “wetware.” In *TAKEOVER: Who is Doing the Art of Tomorrow (Ars Electronica 2001)*, pages 148-152. Springer, 2001.

Implication of wetware

- Works in aquatic environment
- Wetware consumes much less energy than any hardware that is currently available.

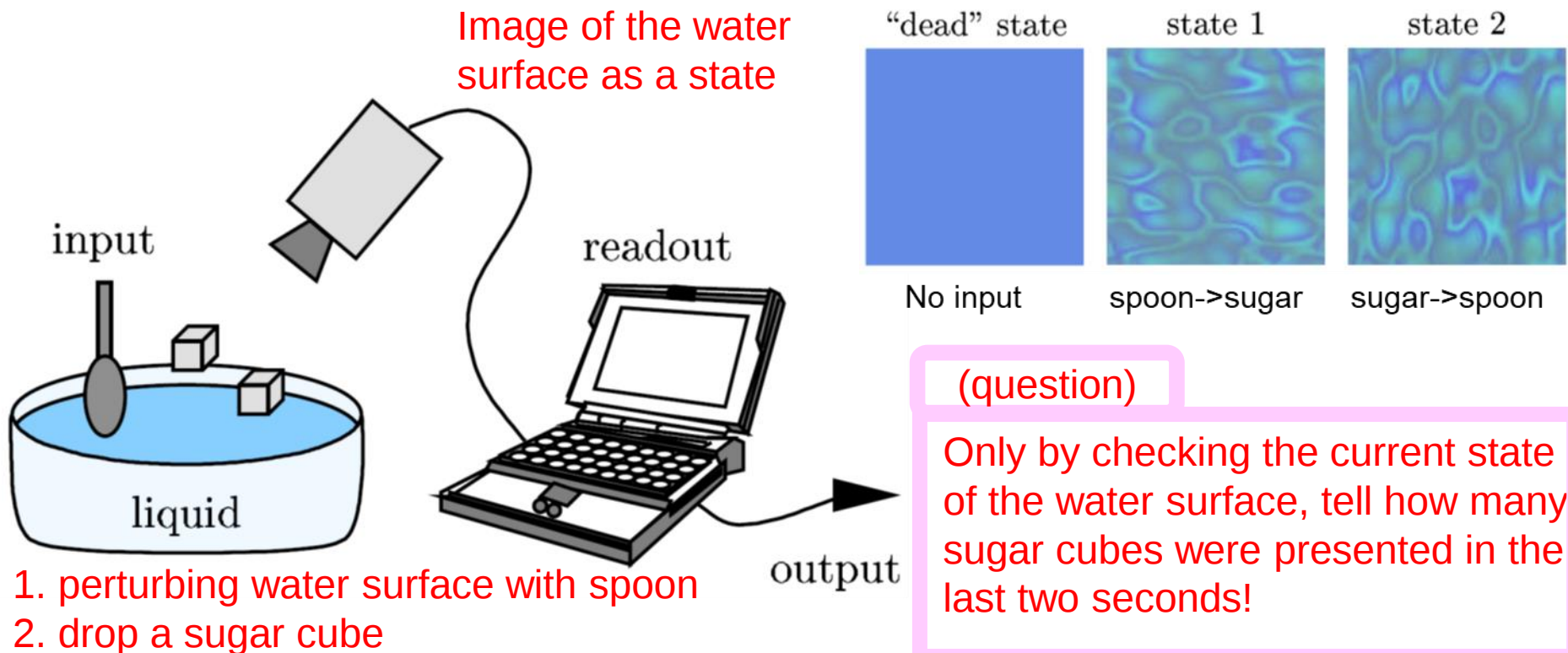
→ effect of embodiment

Once computation “ f ” was implemented in the real-world through a physical substrate, a novel property/functionality is added.

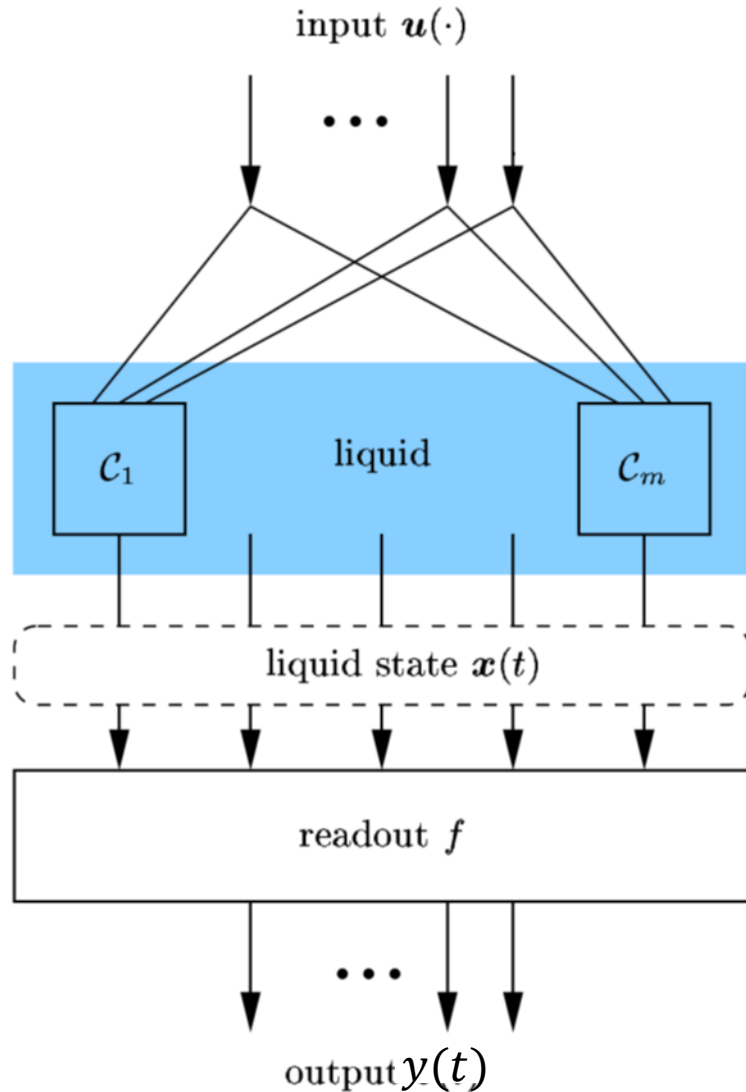
→ more than f

Liquid computer (Natschlaeger-Maass-Markram)

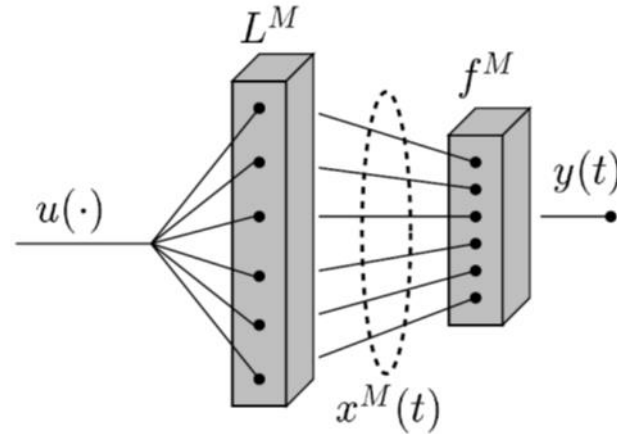
- Brain is receiving sensory stream constantly. No stable states (except a "dead state").
- Like a water surface with constant external perturbations.
- Consider as a filter mapping input stream to output stream.



Liquid state machine: formalizing liquid computer



T. Natschlaeger, W. Maass, and H. Markram. *Special Issue on Foundations of Information Processing of TELEMATIK*, 8(1):39-43, 2002.



Maass, W., Natschläger, T., & Markram, H. (2002), *Neural computation*, 14(11), 2531-2560.

Maass, W., Markram, H. *Journal of computer and system sciences*, 69(4), 593-616, 2004.

Boyd S, Chua L (1985) *IEEE Trans Circuits Syst* 32(11):1150–1161

L^M : liquid filter

x^M : liquid state

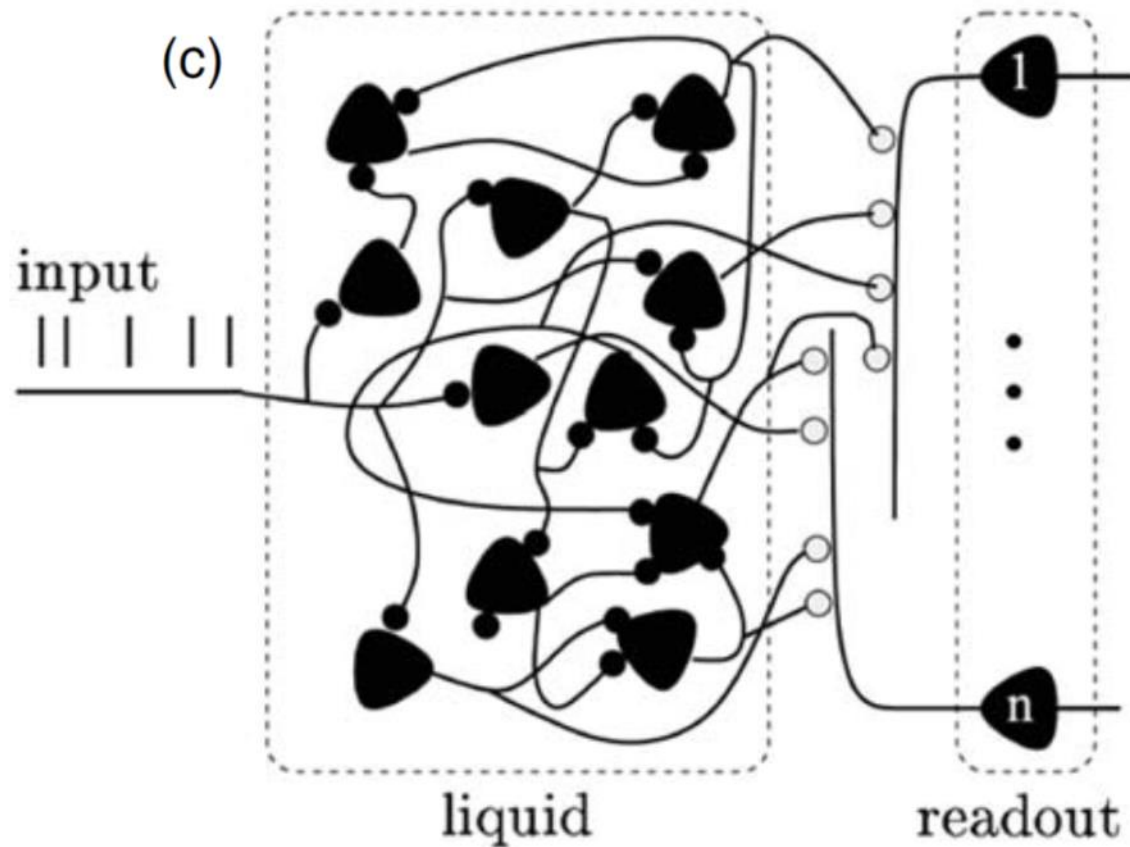
f^M : readout map

$$x^M(t) = (L^M u)(t)$$

(liquid state is a function of input)

$$y(t) = f^M(x^M(t))$$

Brain as liquid state machine



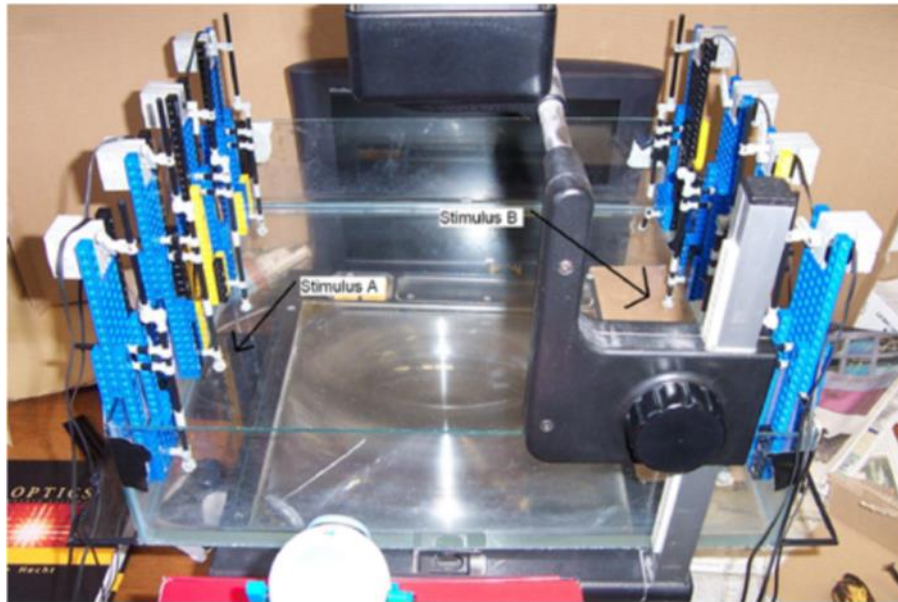
T. Natschlaeger, W. Maass, and H. Markram. *Special Issue on Foundations of Information Processing of TELEMATIK*, 8(1):39-43, 2002.

- Formulation is not based on neurons!

Liquid brain (Fernando-Sojakka)

Here we have taken the metaphor seriously and demonstrated that real water can be used as an LSM for solving the XOR problem and undertaking speech recognition in the Hopfield and Brody “zero-one” discrimination [2]. Doing so

Fernando, C., & Sojakka, S. (2003, September). Pattern recognition in a bucket. In European conference on artificial life (pp. 588-597). Springer, Berlin, Heidelberg.



Input: Four mechanical components with motors in each side, perturbing the water surface.

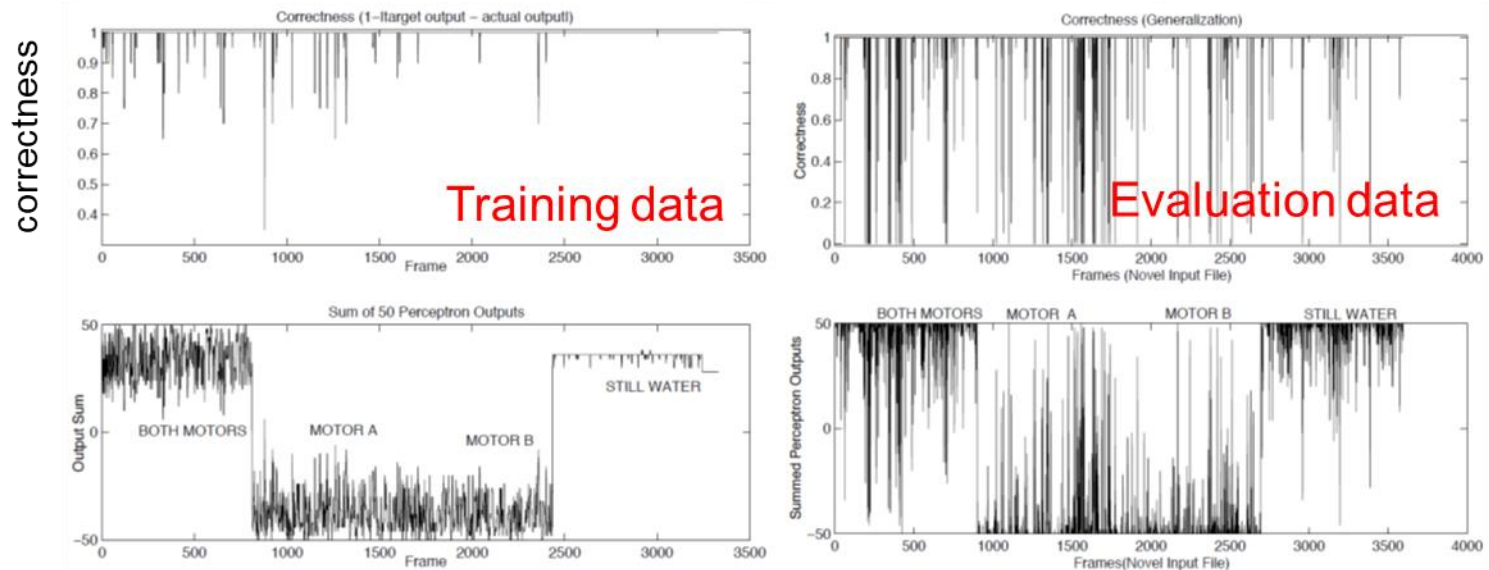
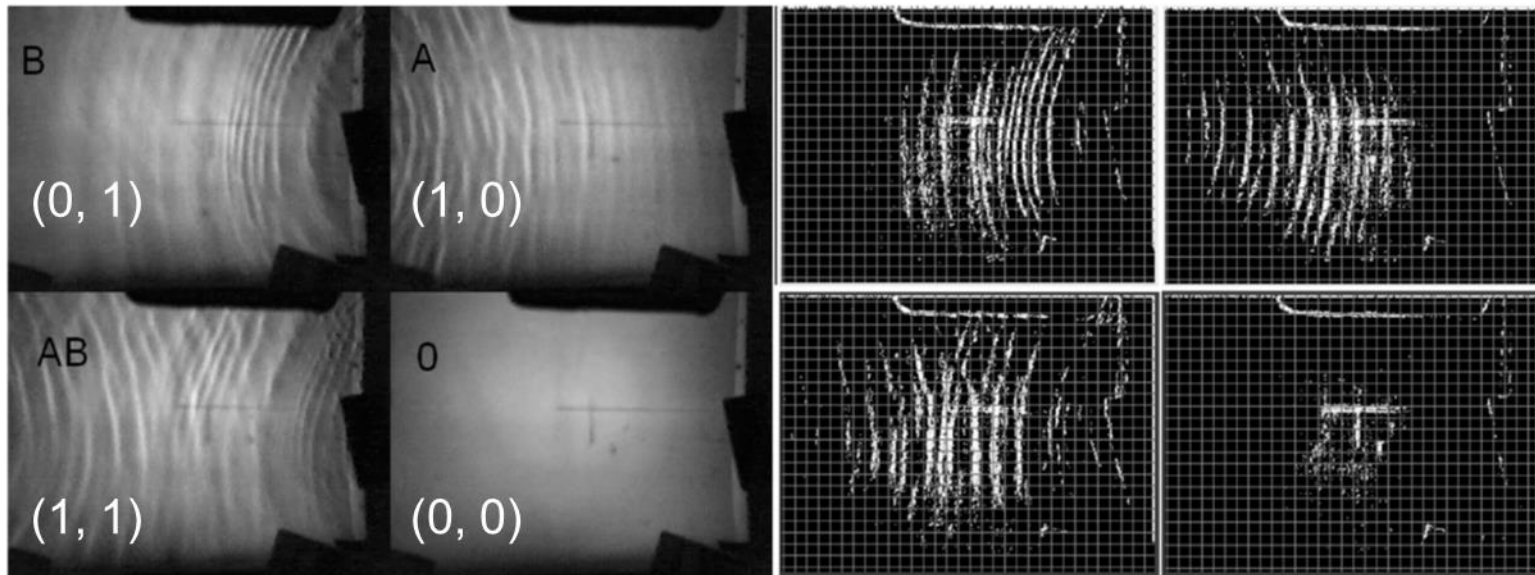
State: Web cam image with preprocessing such as discretization to grid (320×240 pixels, 5Hz).

Output: Perceptron with 50 nodes

(tasks) The liquid brain

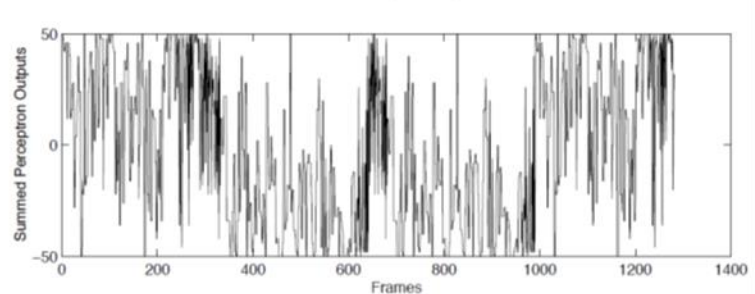
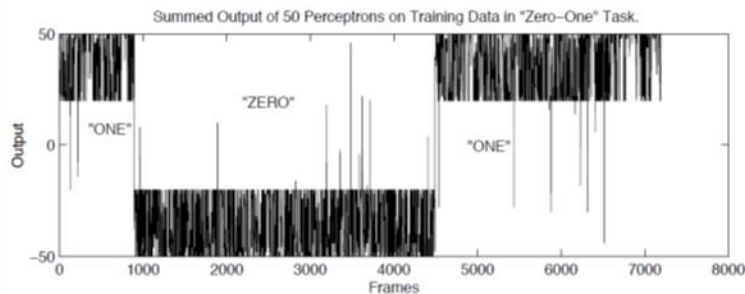
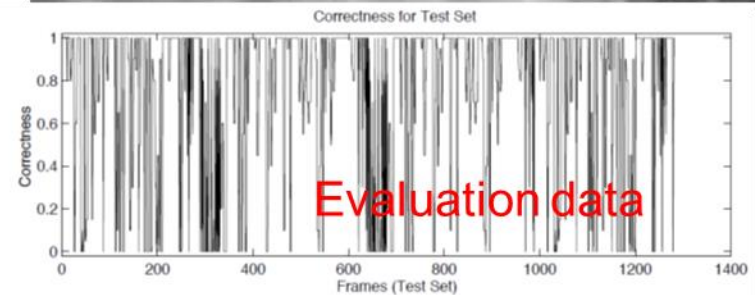
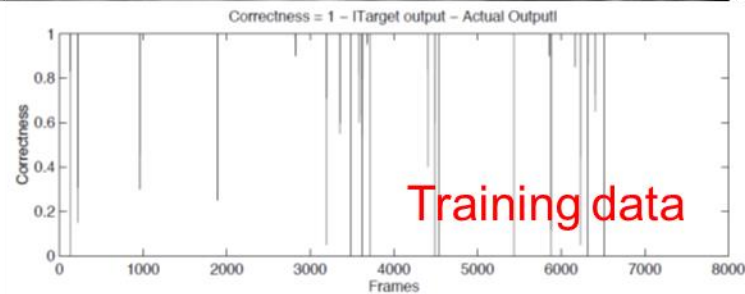
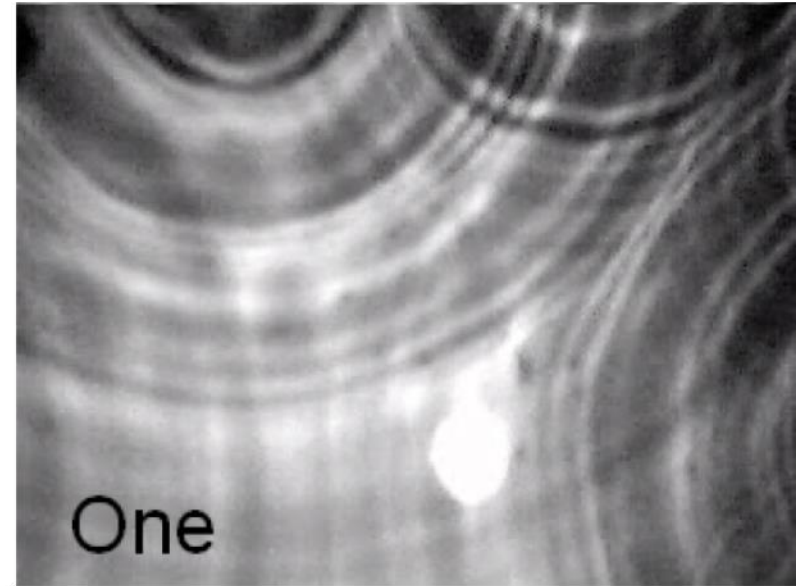
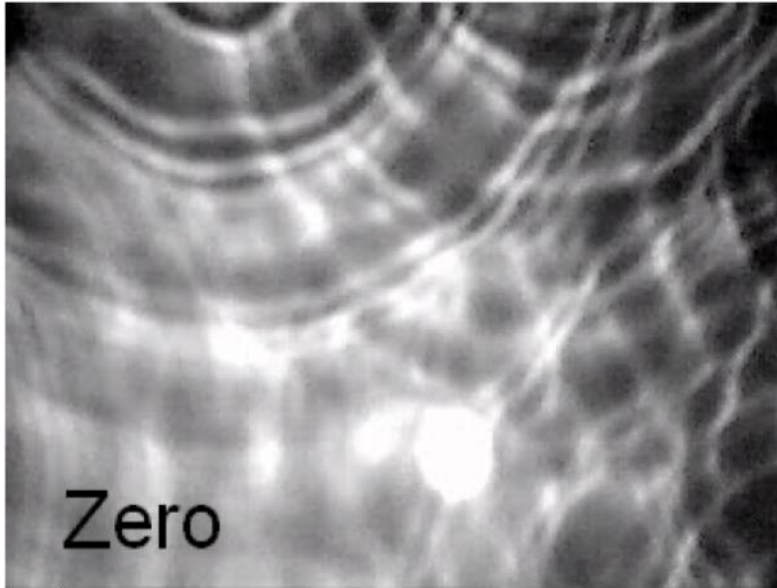
- **XOR task:** perturb with “left motors”=(1, 0), “right motors”=(0, 1), “both motors/none”=(1, 1)/(0, 0)
- **Speech recognition:** sound data “one”, “zero” are temporary discretized into 8 segments. After applying finite time Fourier transform, discretizing frequency into 8 segments. Using 8×8 matrix as input.

Results: XOR task



accuracy: 85% in evaluation phase

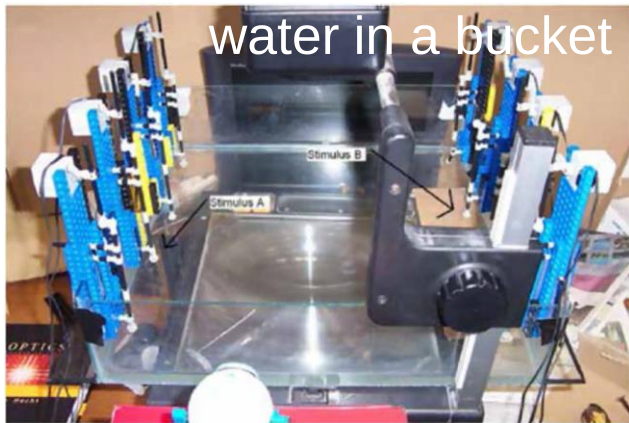
Results: Speech recognition



accuracy: 35% in evaluation phase

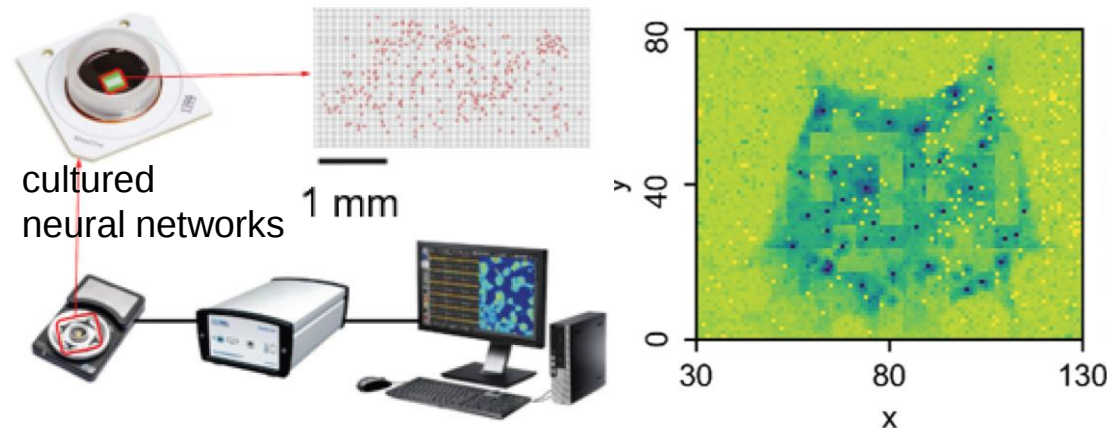
Physical reservoirs ...

Liquid brain



C. Fernando et. al., Lec. Comp. Sci. 2801 (2003).

Cultured neural networks

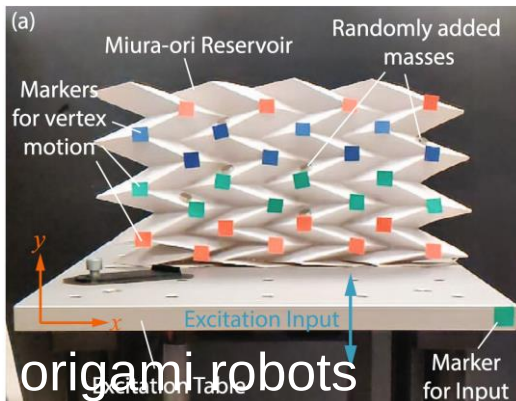


M. R. Dranias, et. al., J. Neurosci. 33, 1940 (2013).

T. Kubota, et. al., Lect. Comp. Sci. 11731 (2019).

Y. Yada, et. al., Appl. Phys. Lett., 119(17), 173701 (2021).

Soft robots



Q. Zhao et al., Proceedings of IROS, pp. 1445-1451 (2013).

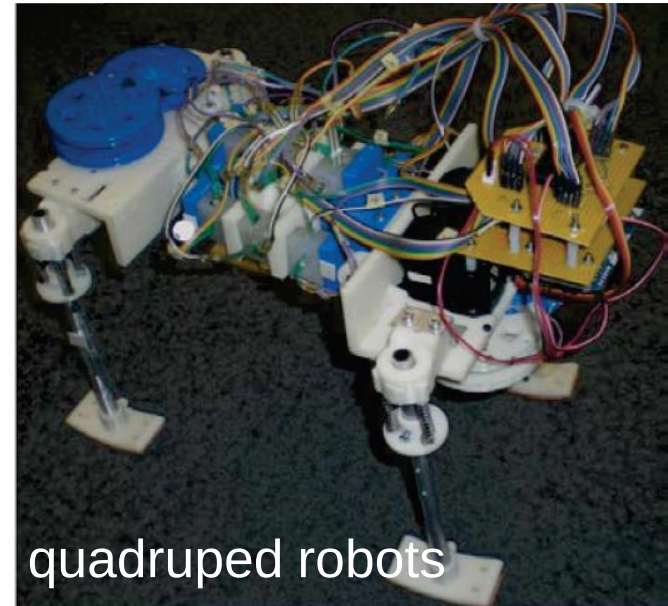
K. Nakajima et al. J. R. Soc. Interface. 11: 20140437 (2014).

K. Caluwaerts et al. J. R. Soc. Interface 11:98 (2014).

K. Nakajima et al. Sci. Rep. 5: 10487 (2015).

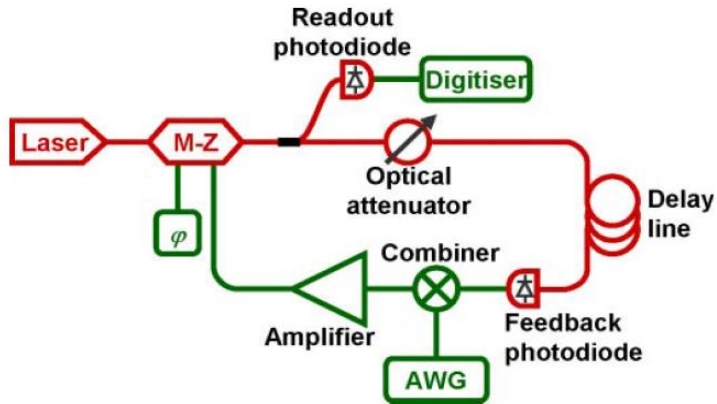
K. Nakajima et al. Soft Robotics 5: 10487 (2018).

P. Bhovad, et. al., Sci. Rep. 11(1), 1-18 (2021).



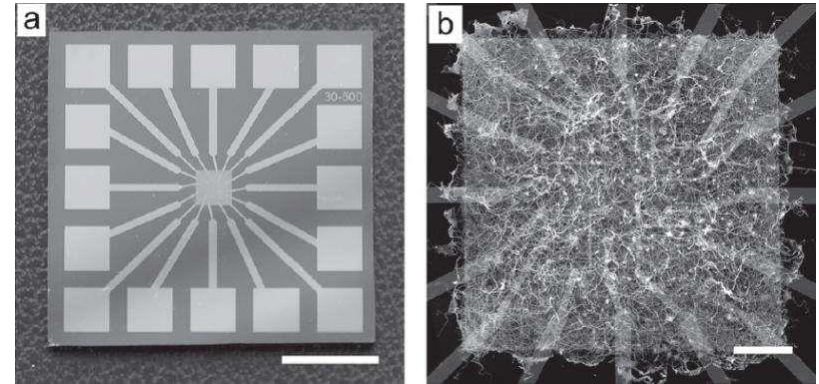
PRC for neuromorphic devices

Photonic reservoirs



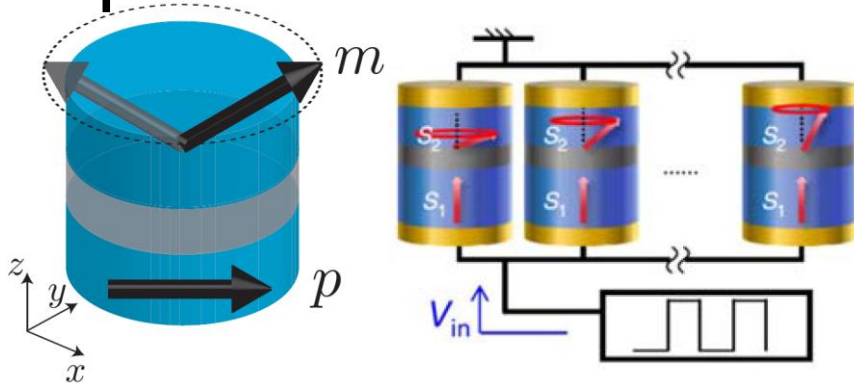
L. Larger, et. al., Opt. Express 20, 3241 (2012).
 D. Brunner, et. al., Nat. Commun. 4, 1364 (2013).
 K. Vandoorne, et. al., Nat. Commun. 5, 3541 (2014).
 L. Larger, et. al., Phys. Rev. X 7, 011015 (2017).
 M. Nakajima et al., Nat. Commun. 13, 7847 (2022).

In-Materia reservoirs



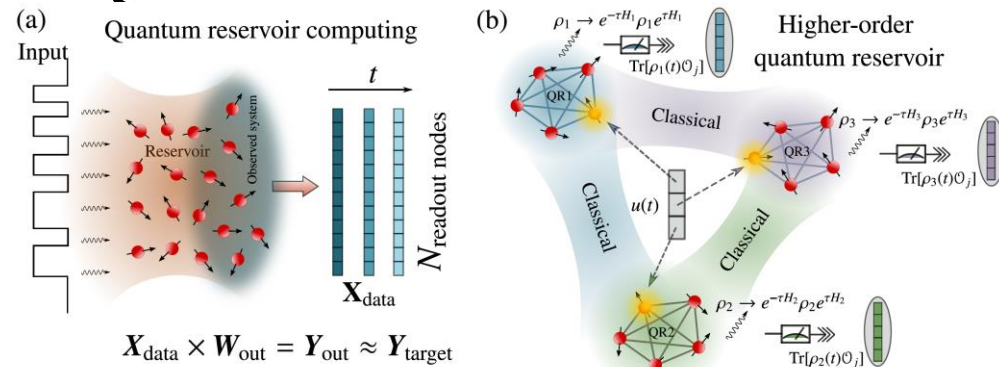
E. C. Demis et al. Nanotechnology 26:204003 (2015).
 A. Z. Stieg et al. Adv. Mater. 24:286-293 (2012).
 M. Cucchi, et. al., Science Advances, 7(34), eabh0693 (2021).
 Y. Usami, et. al., Adv. Mater. (2021).

Spintronics reservoirs



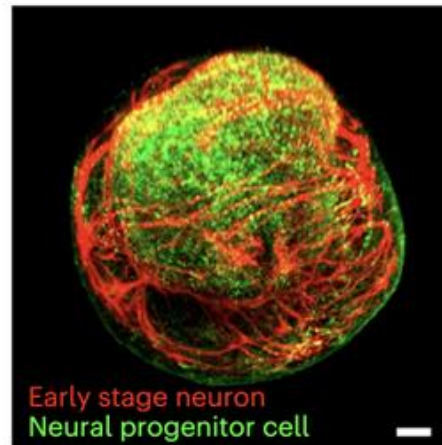
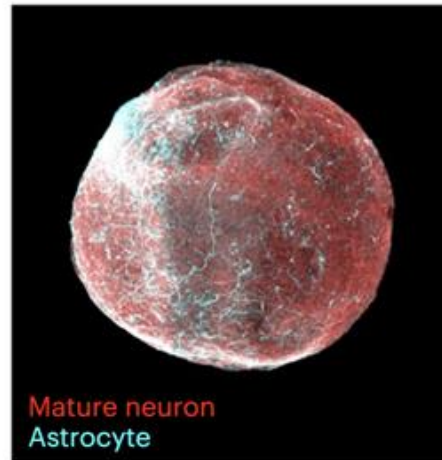
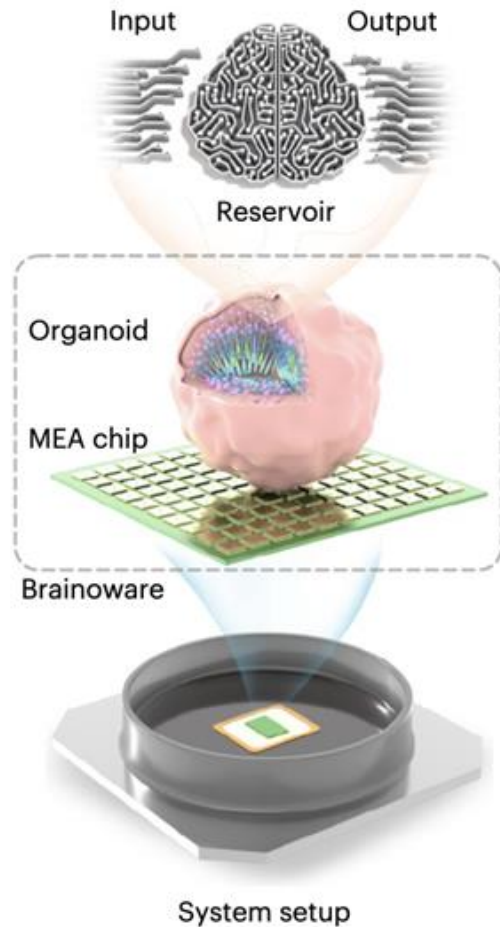
J. Torrejon et al., Nature 547, 428 (2017).
 T. Furuta, et. al., Phys. Rev. Appl. 10, 034063 (2018).
 S. Tsunegi, et. al., Appl. Phys. Lett. 114, 164101 (2019).
 N. Akashi, et. al., Phys. Rev. Res. 2: 043303 (2020).
 Lee, O., Wei, T., Stenning, K.D. et al. Nat. Mater. (2023).

Quantum reservoirs



K. Fujii, K. Nakajima, Phys. Rev. Appl. 8: 024030 (2017).
 K. Nakajima, et. al., Phys. Rev. Appl. 11: 034021 (2019).
 S. Ghosh, et. al., Adv. Quantum Technol. 4: 2100053 (2021).
 Q. H. Tran, K. Nakajima, Phys. Rev. Lett. 127: 260401 (2021).
 T. Kubota et al., Phys. Rev. Res., 5(2), 023057 (2023)..

Brain Organoid Reservoir Computing



...We illustrate the practical potential of this technique by using it for speech recognition and nonlinear equation prediction in a ***reservoir computing framework***.

Cai, H., Ao, Z., Tian, C., Wu, Z., Liu, H., Tchieu, J., ... & Guo, F. (2023). Brain organoid reservoir computing for artificial intelligence. *Nature Electronics*, 6(12), 1032-1039.

A unicellular organism as a reservoir!

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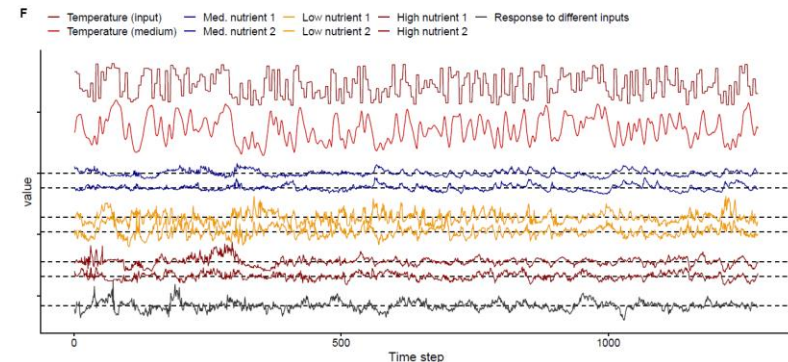
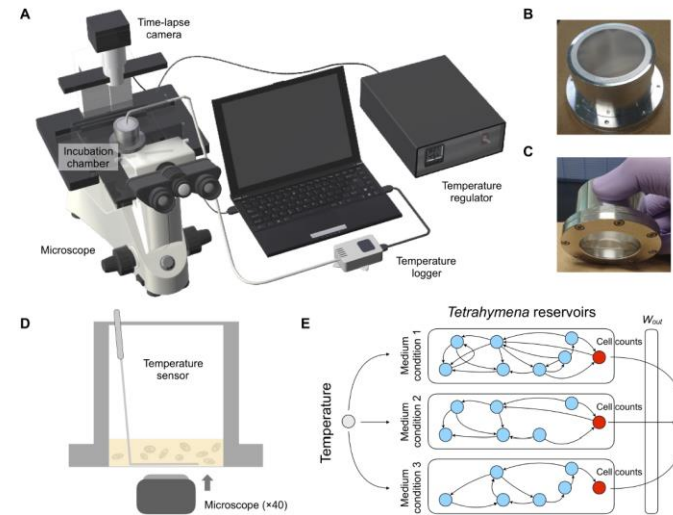
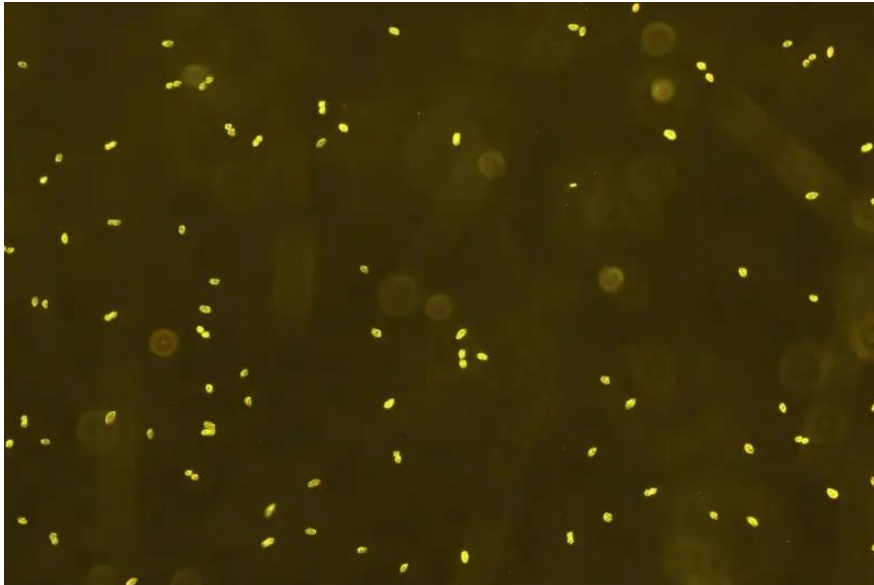
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Biological computer made from single-celled organisms can crunch data

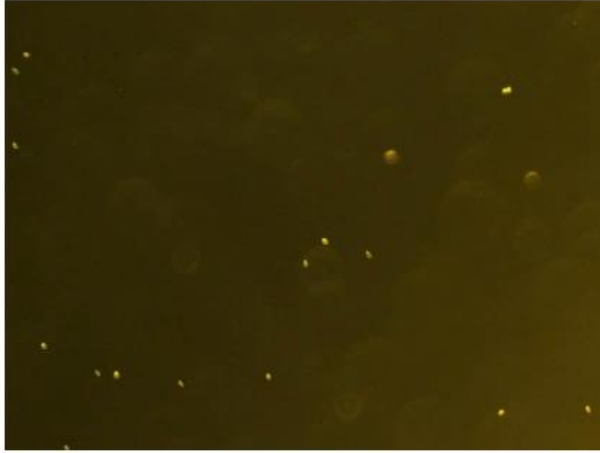


M. Ushio, K. Watanabe, Y. Fukuda, Y. Tokudome, K. Nakajima, Computational capability of ecological dynamics, doi:

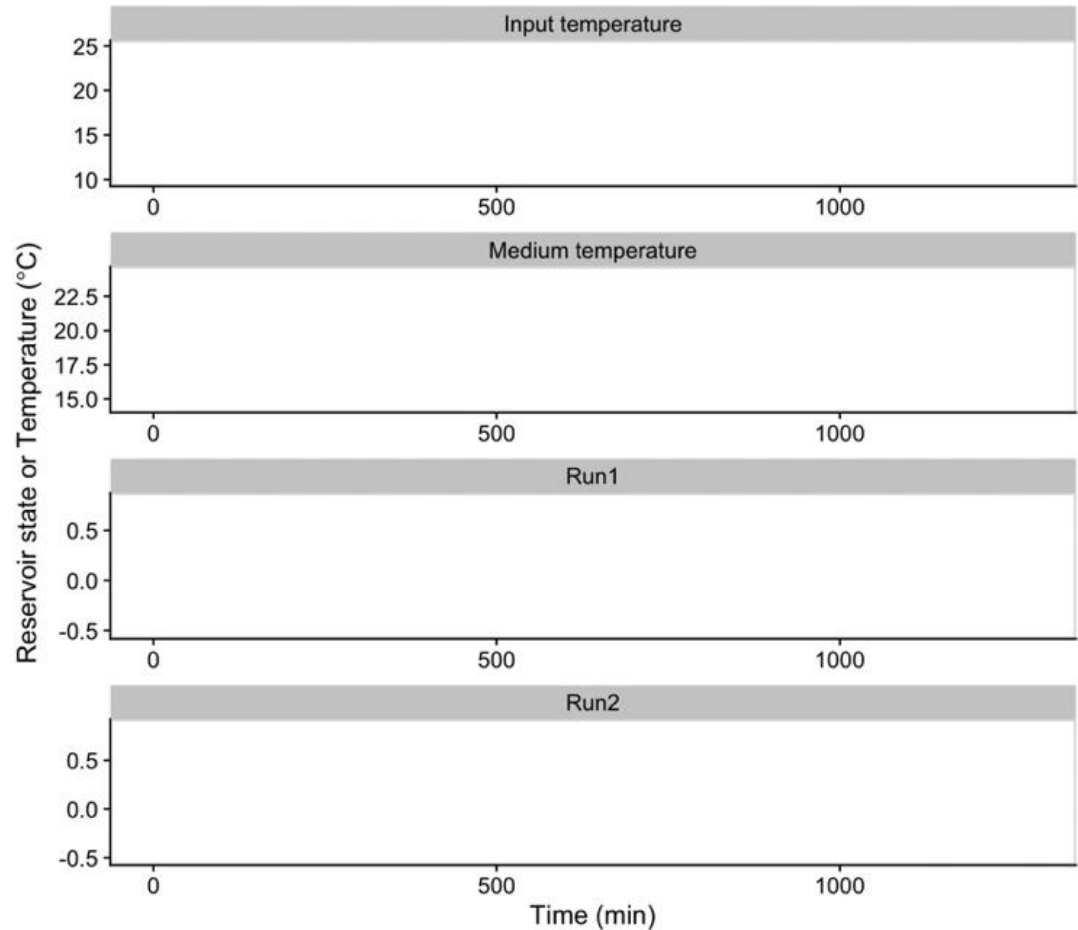
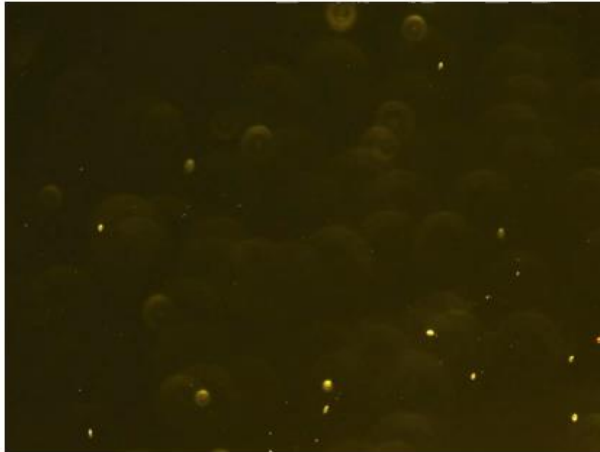
<https://doi.org/10.1101/2021.09.15.460556>

Common-signal-induced synchronization in ecological dynamics: *Tetrahymena thermophila*

Medium nutrient concentration - Run1

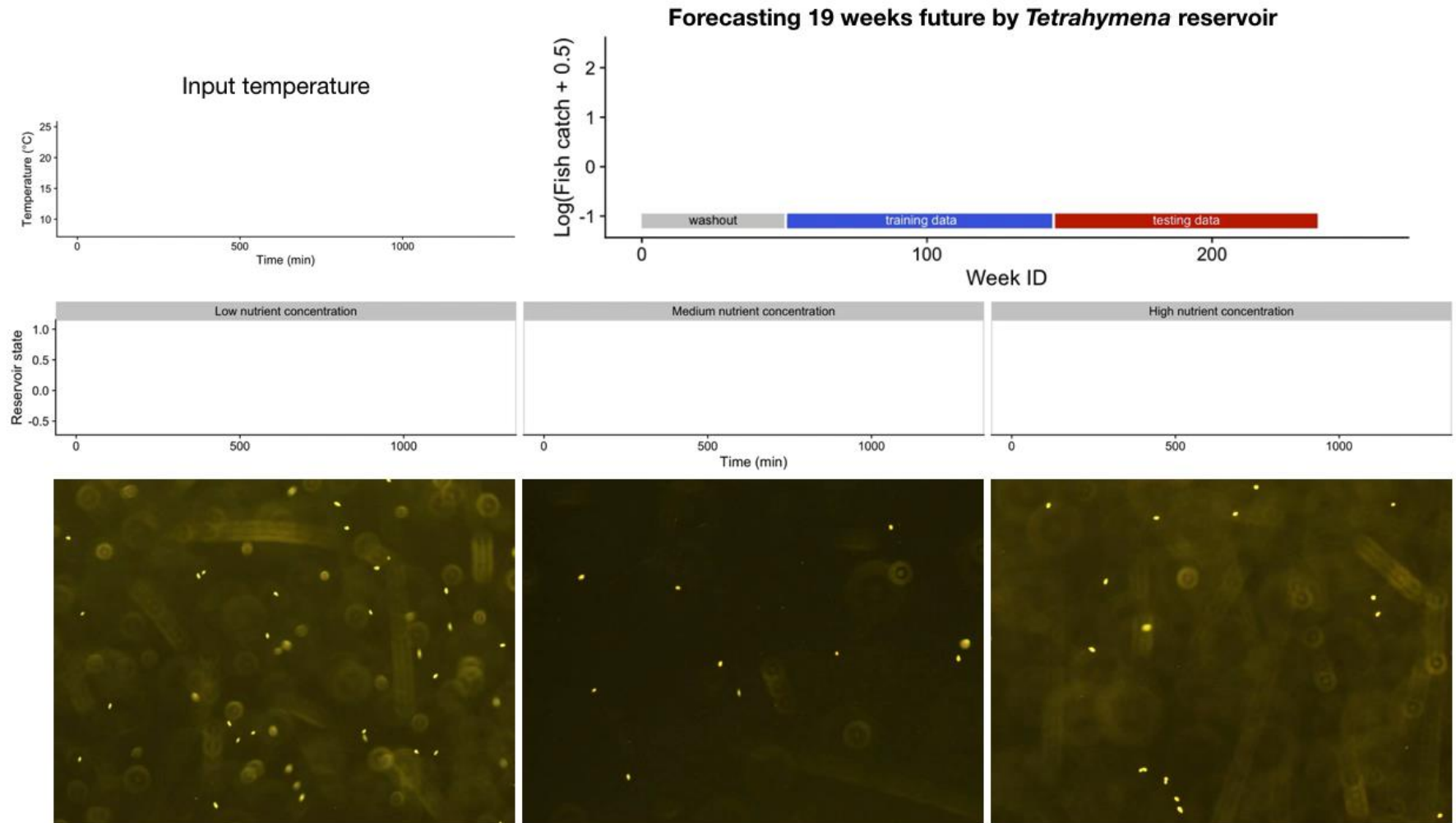


Medium nutrient concentration - Run2



M. Ushio, K. Watanabe, Y. Fukuda, Y. Tokudome, K. Nakajima, Computational capability of ecological dynamics, Royal Society Open Science, 10(4), 221614

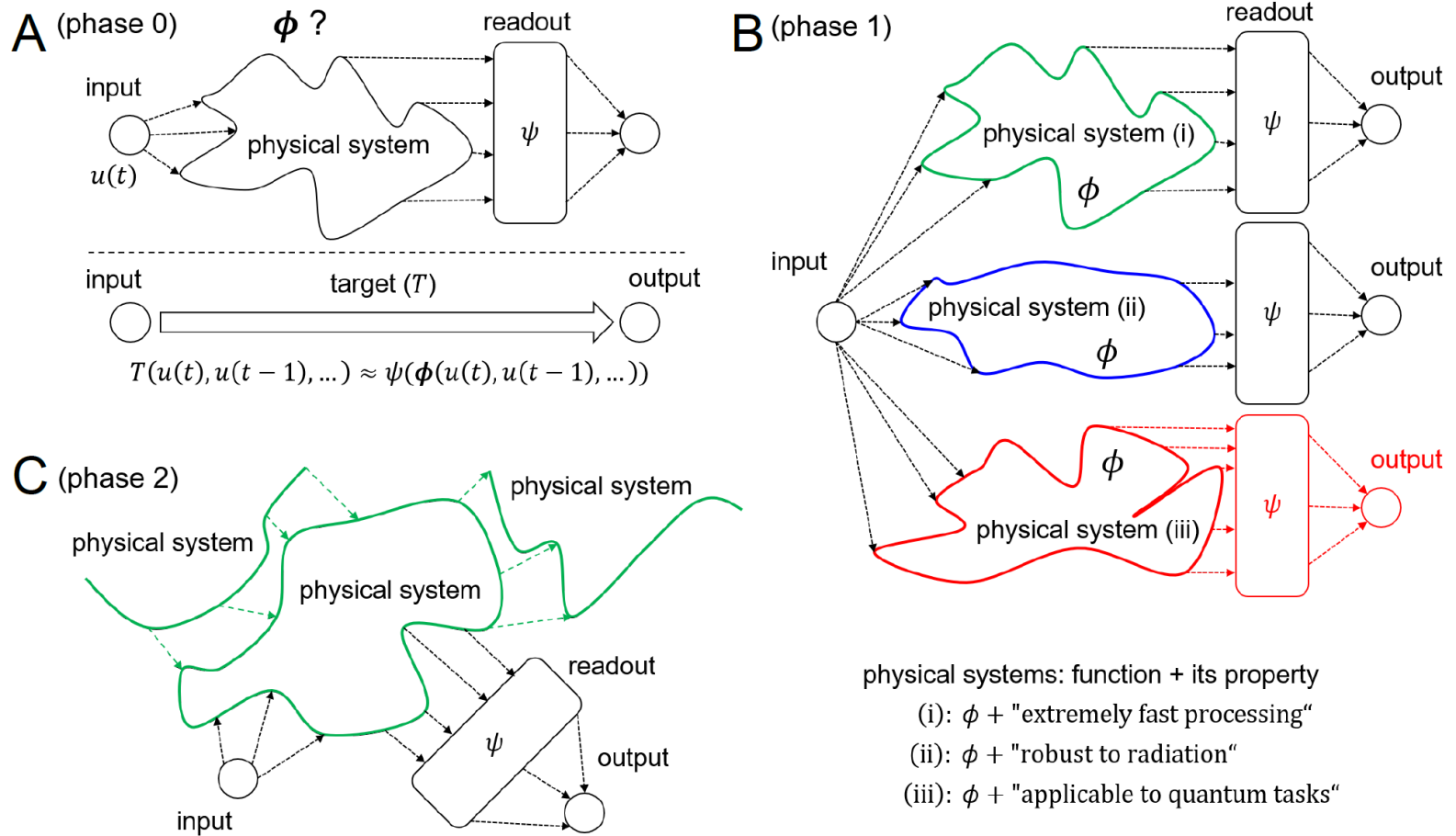
Prediction of fish population dynamics (*Flatfish*)



M. Ushio, K. Watanabe, Y. Fukuda, Y. Tokudome, K. Nakajima, Computational capability of ecological dynamics, Royal Society Open Science, 10(4), 221614 (2023).

What is specific in PRC?

Nakajima, K. (2020). Physical reservoir computing—an introductory perspective. Jap. J. Appl. Phys., 59(6), 060501.



A: Inferring the computational power of physical systems.

B: Physical properties of a computer.

C: Exploiting a physical substrate that is not made for computation for computation.

Physical reservoir computing for soft robots

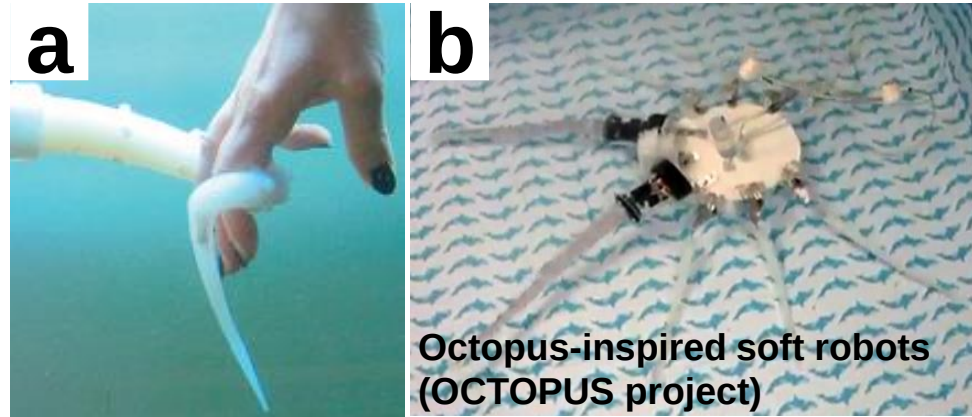
Soft robotics: Robots made of soft materials

Octopus

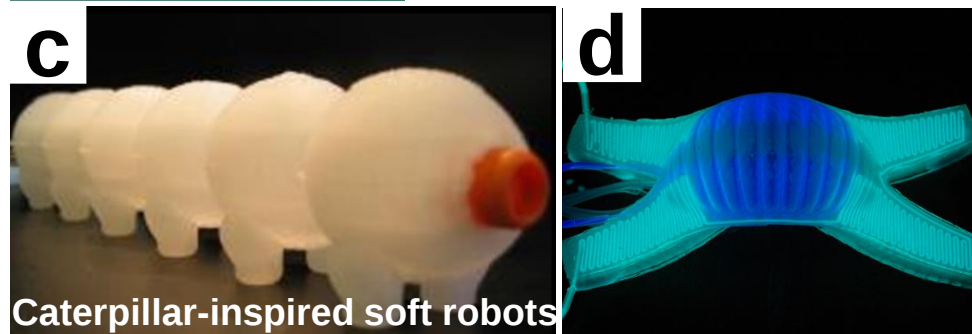


(EU project: ICT-FET OCTOPUS Integrating Project)

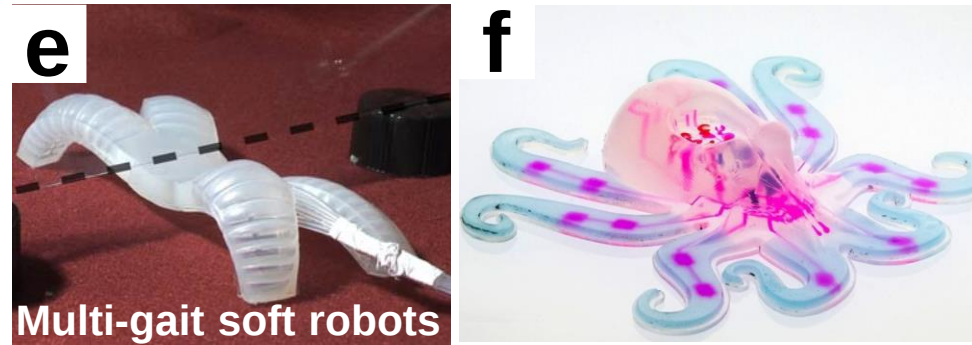
Soft robots



Octopus-inspired soft robots (OCTOPUS project)



Caterpillar-inspired soft robots



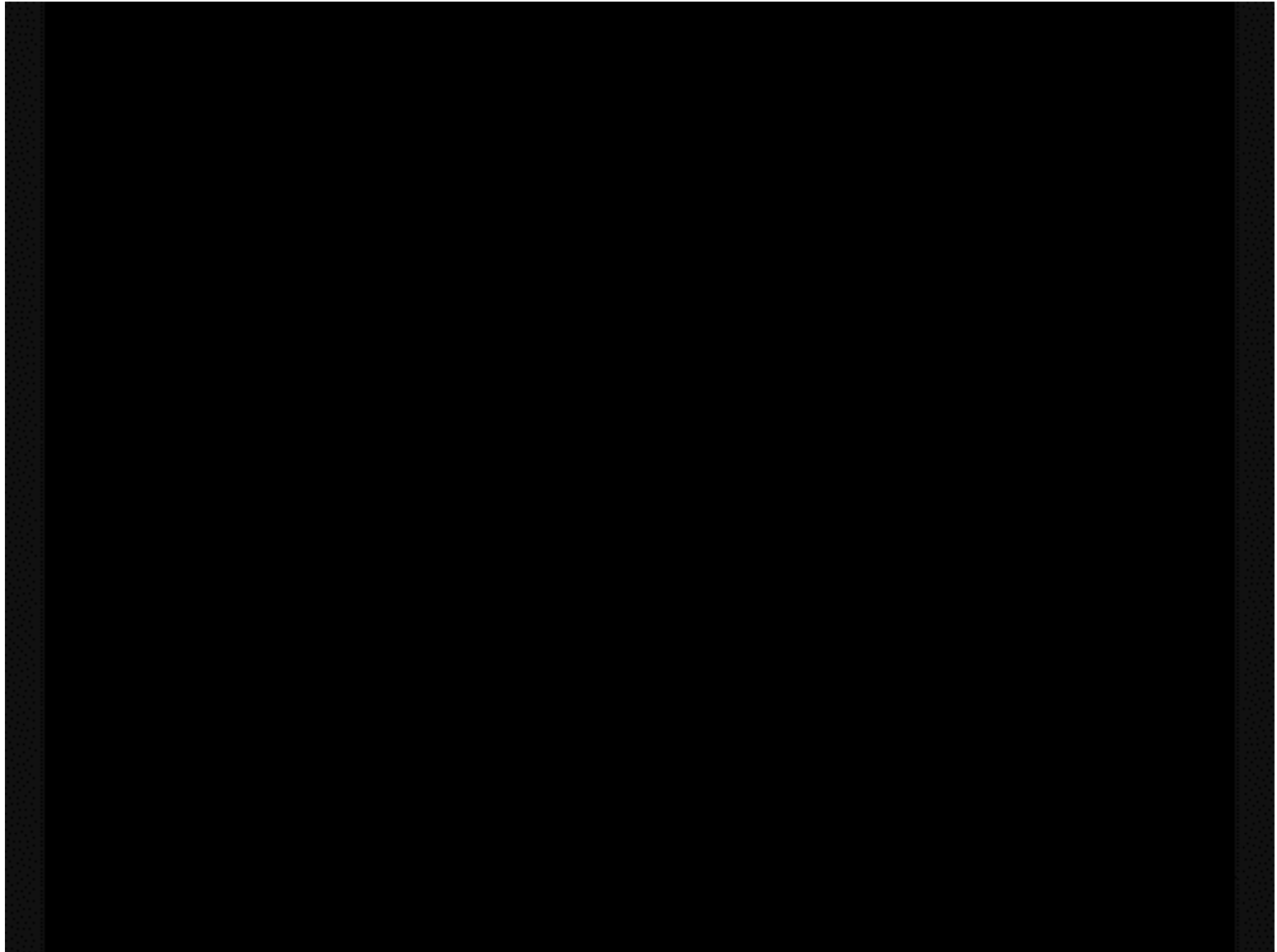
Multi-gait soft robots

Good points

- Deformability
- Interactional safety

a. Cianchetti, M., et. al., Mater. Sci. Eng., C, 31, 1230-1239, 2011.. b. "Robotic Octopus Takes First Tentacled Steps", IEEE spectrum, 9 Apr 2012. c. "GoQBot: A caterpillar-inspired soft-bodied rolling robot.", Lin, H.-T., et. al., Bioinsp. Biomim., 6(2), 2011. d. "Camouflage and Display for Soft Machines", Morin, S.A., et. al., Science, 2012, 337, 828-832. e. "Multi-Gait Soft Robot", Shepherd, R.F., et. al., PNAS, 108, 20400-20403, 2011. f. Nature 536, 451-455 (2016)

Octopus swimming robot (sculling)



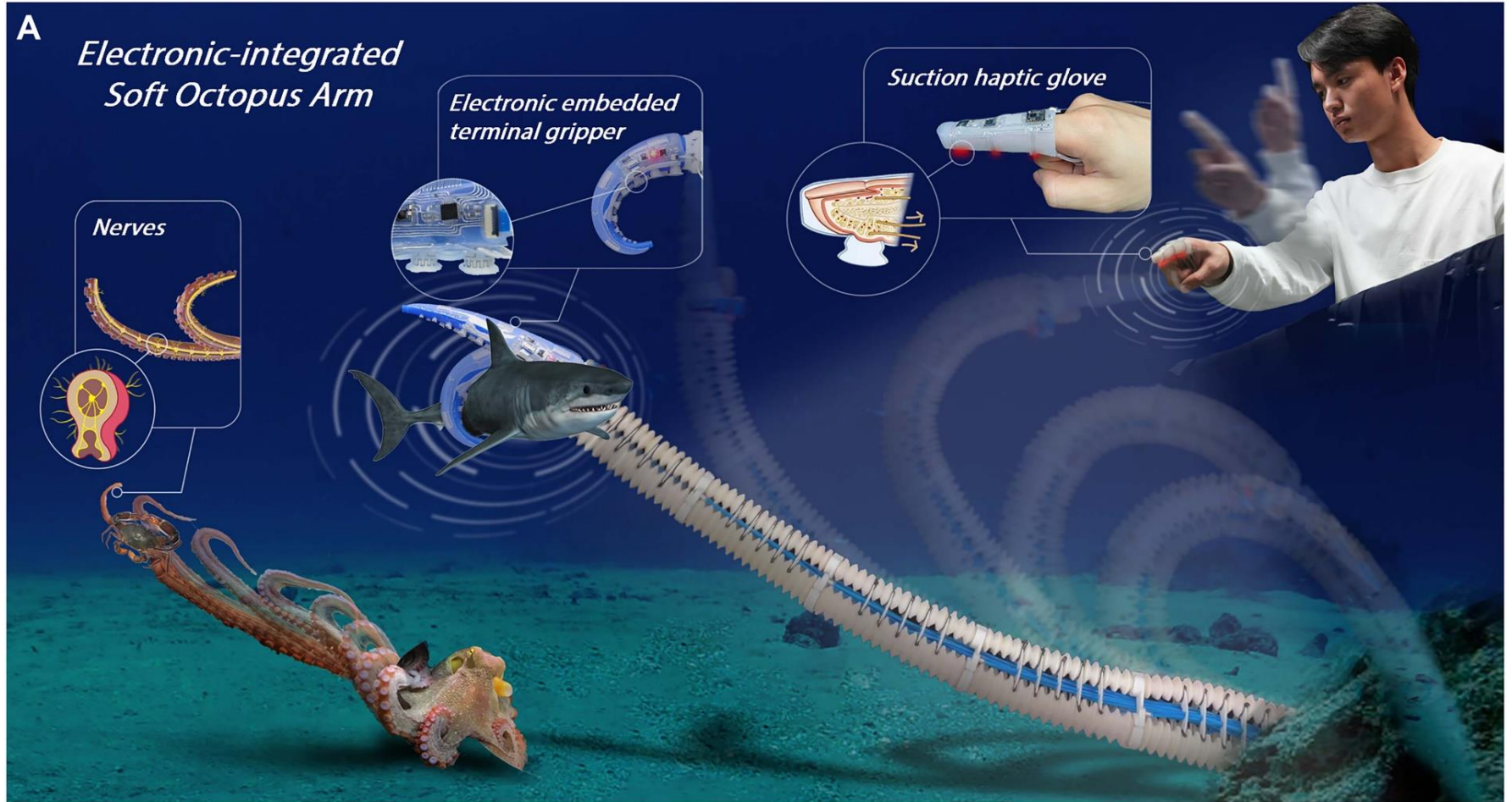
(*Sculling' Inspires Creation Of Robot Octopus* IEEE spectrum, 2013, by
Sfakiotakis, M., Kazakidi, A., Pateromichelakis, N., Tsakiris)

Multi-gait soft robot



("Multi-Gait Soft Robot", Shepherd, R.F., et. al., PNAS, 108, 20400-20403, 2011)

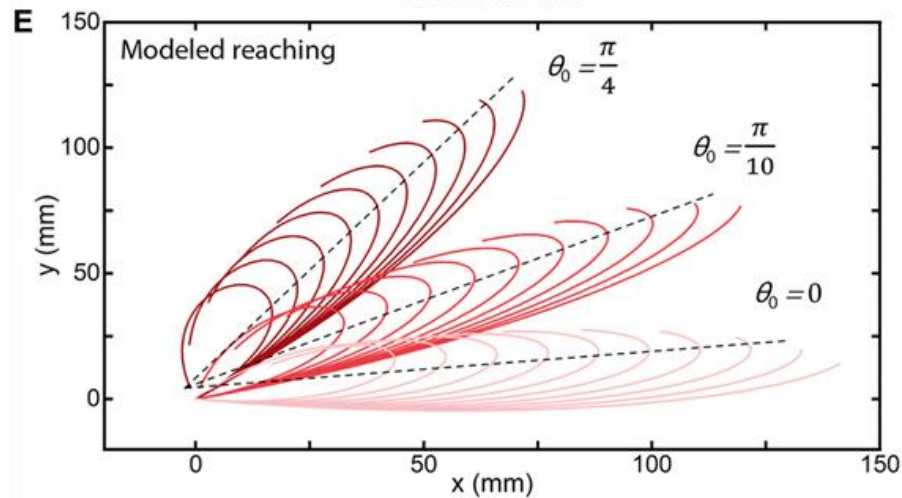
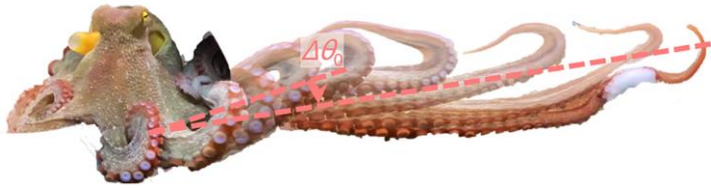
Octopus-inspired sensorized soft arm for environmental interaction



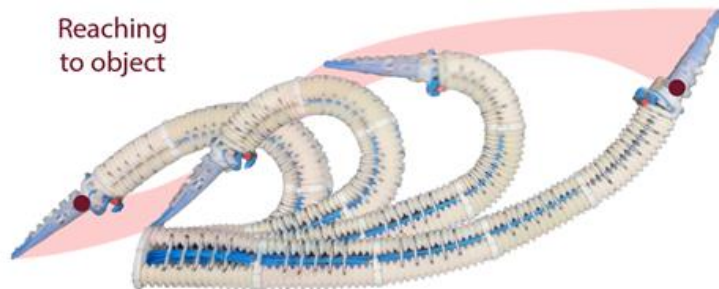
Zhexin Xie et al. ,Octopus-inspired sensorized soft arm for environmental interaction. Sci. Robot.8,eadh7852(2023). **Nov 29, 2023** DOI:10.1126/scirobotics.adh7852

Octopus-inspired reaching and fetching control

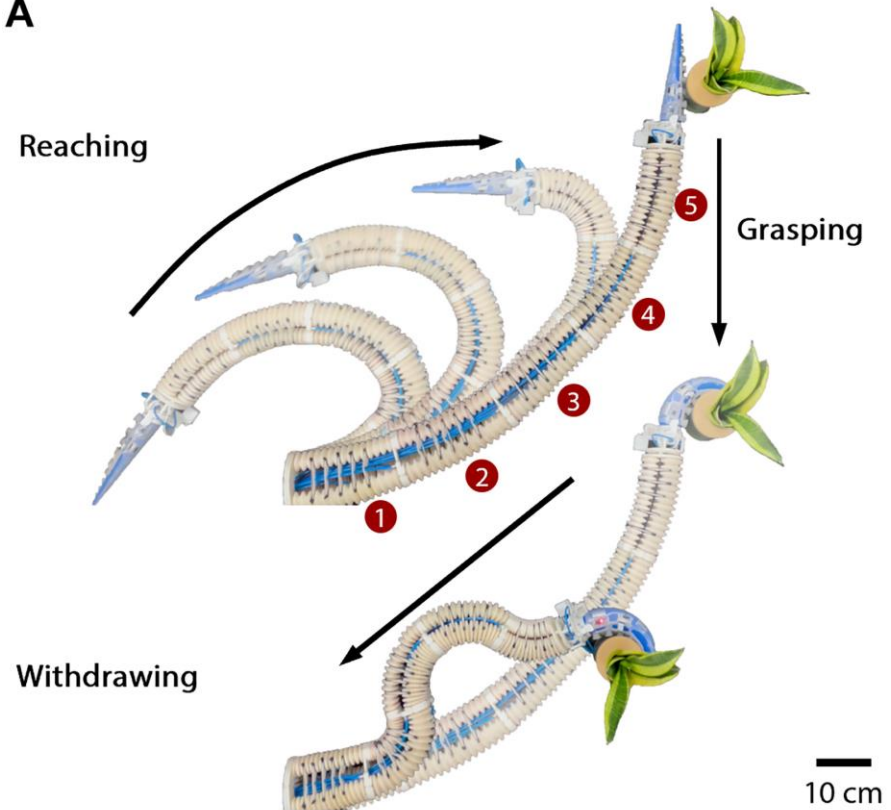
A Reaching motion



G



A



Pneumatic actuators!

Octopus reaching

Movie S6

Biology octopus reaching motion

Octopus-inspired sensorized soft arm for environmental interaction

Z. Xie†, F. Yuan†, J. Liu†, L. Tian†, B. Chen, Z. Fu, S. Mao, T. Jin, Y. Wang, X. He, G. Wang, Y. Mo, X. Ding, Y. Zhang, C. Laschi, L. Wen*

Movie S9

Robotic octopus arm reaching and grasping an object

Octopus-inspired sensorized soft arm for environmental interaction

Z. Xie[†], F. Yuan[†], J. Liu[†], L. Tian[†], B. Chen, Z. Fu, S. Mao, T. Jin, Y. Wang, X. He, G. Wang, Y. Mo, X. Ding, Y. Zhang, C. Laschi, L. Wen^{*}

Movie S1

Human controlled underwater 3D manipulation of the robotic octopus arm

Octopus-inspired sensorized soft arm for environmental interaction

Z. Xie†, F. Yuan†, J. Liu†, L. Tian†, B. Chen, Z. Fu, S. Mao, T. Jin, Y. Wang, X. He, G. Wang, Y. Mo, X. Ding, Y. Zhang, C. Laschi, L. Wen*

Soft robots are difficult to control!

Bad points

- Nonlinearity
- Memory

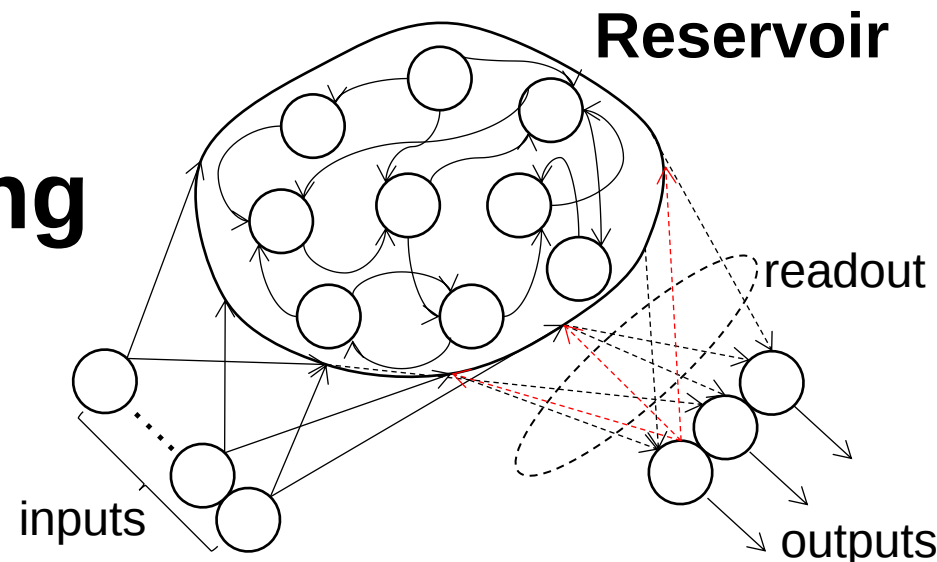


Soft body dynamics

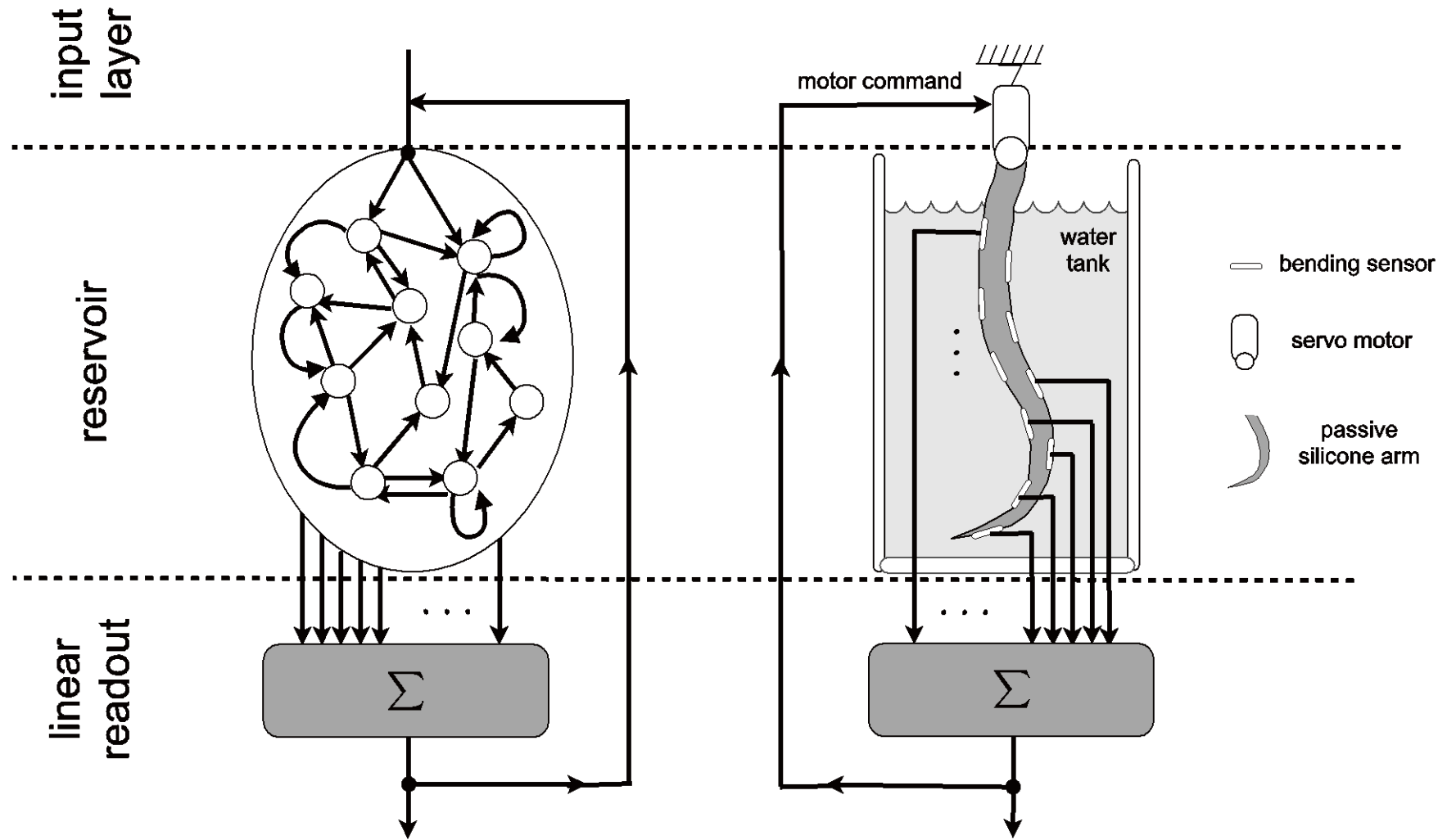
Excellent match?

Reservoir computing

- Nonlinearity
- Memory



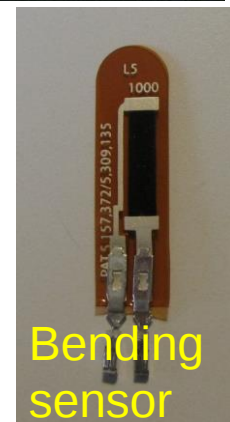
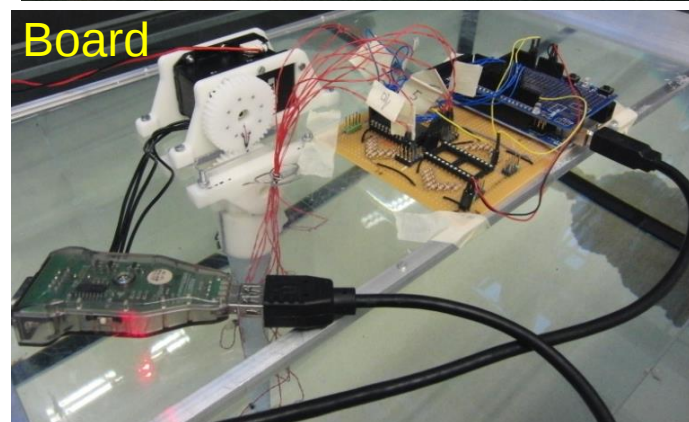
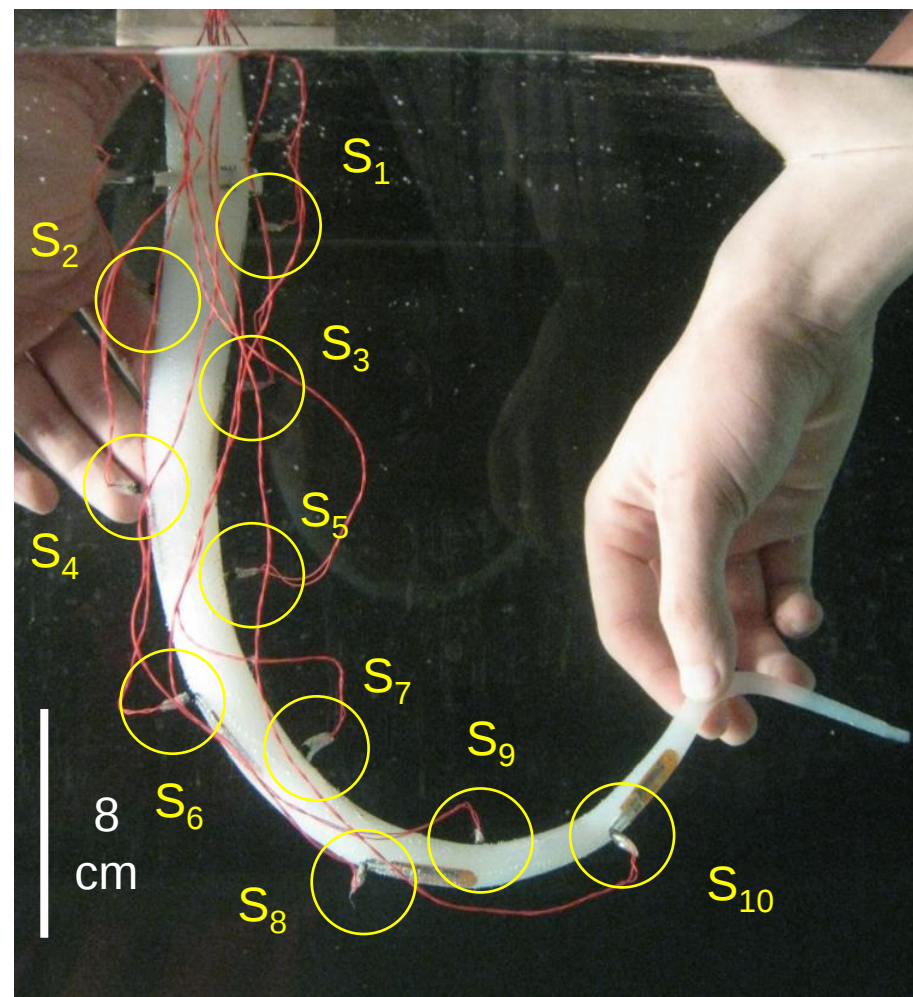
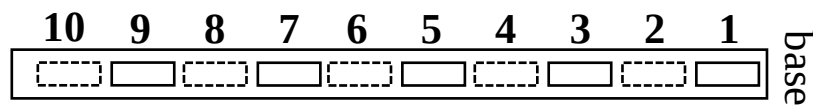
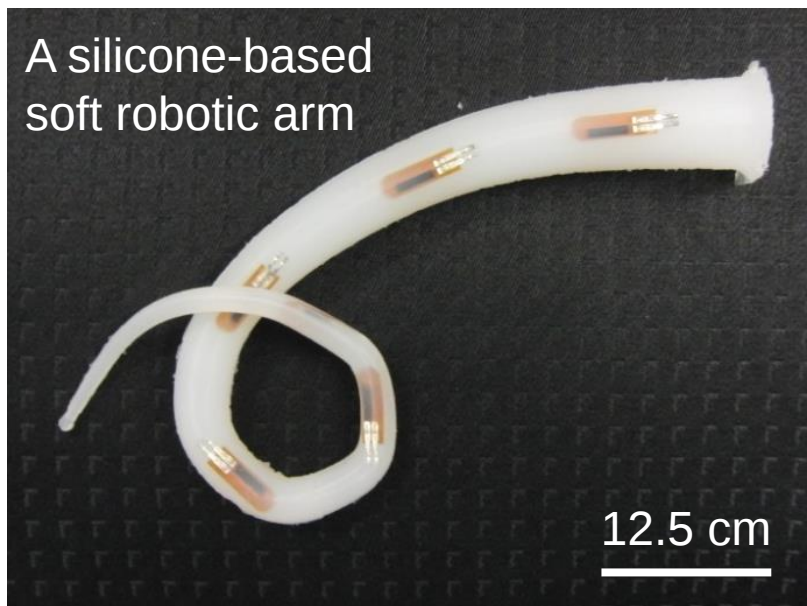
Physical Reservoir Computing



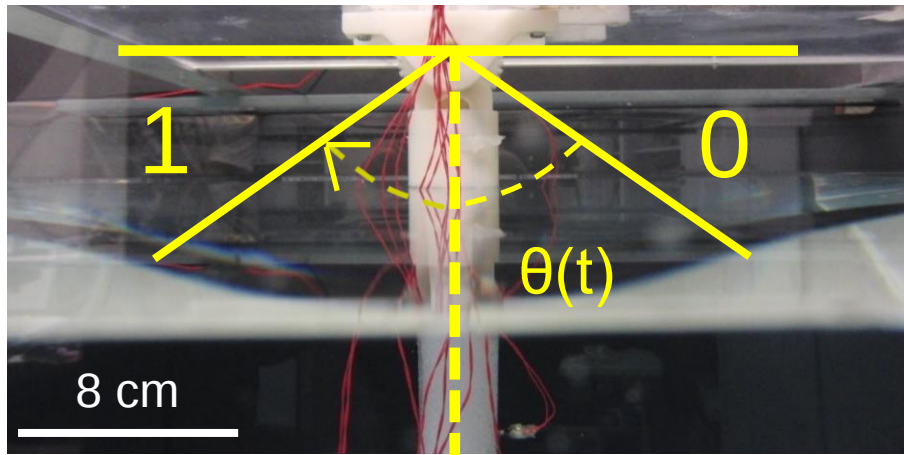
K. Nakajima et. al., *Front. Comput. Neurosci.*, 7 (91), 2013.
K. Nakajima et. al., *J. R. Soc. Interface* 11: 20140437, 2014.
K. Nakajima et. al., *Scientific Reports* 5: 10487, 2015.
K. Nakajima et. al., *Soft Robotics* 5(3): pp.339-347, 2018.

**Soft body dynamics as
computational resource!**

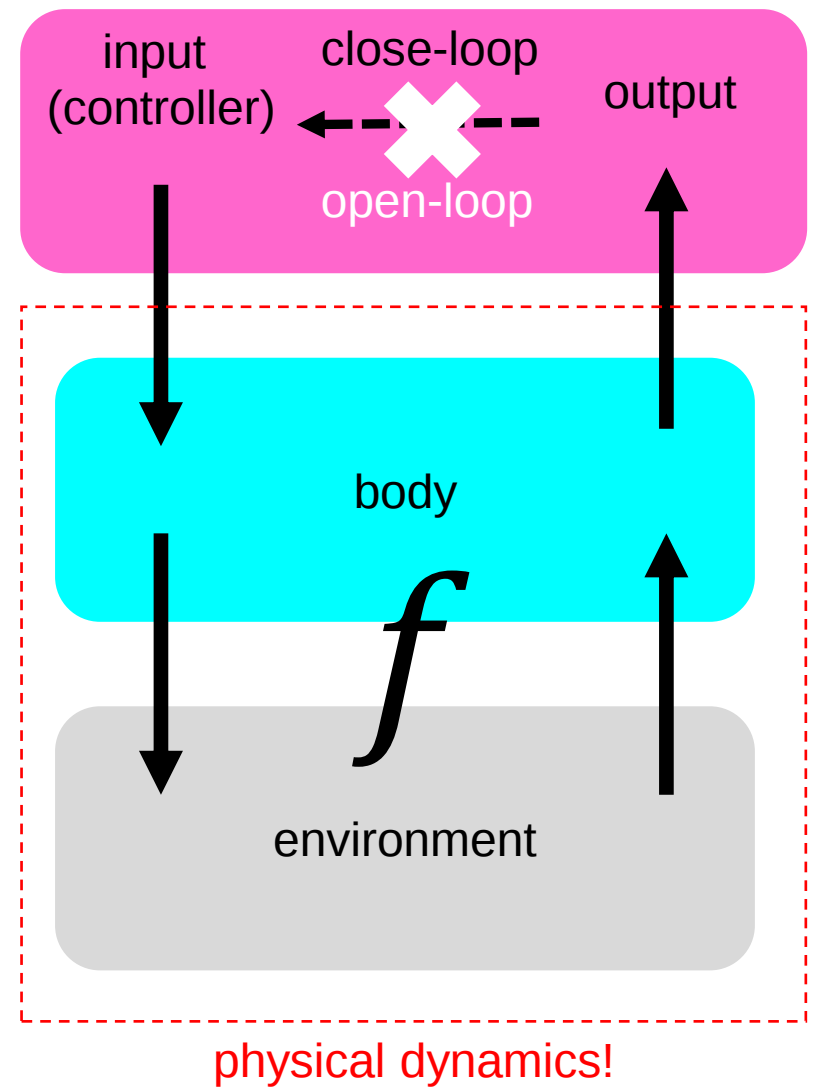
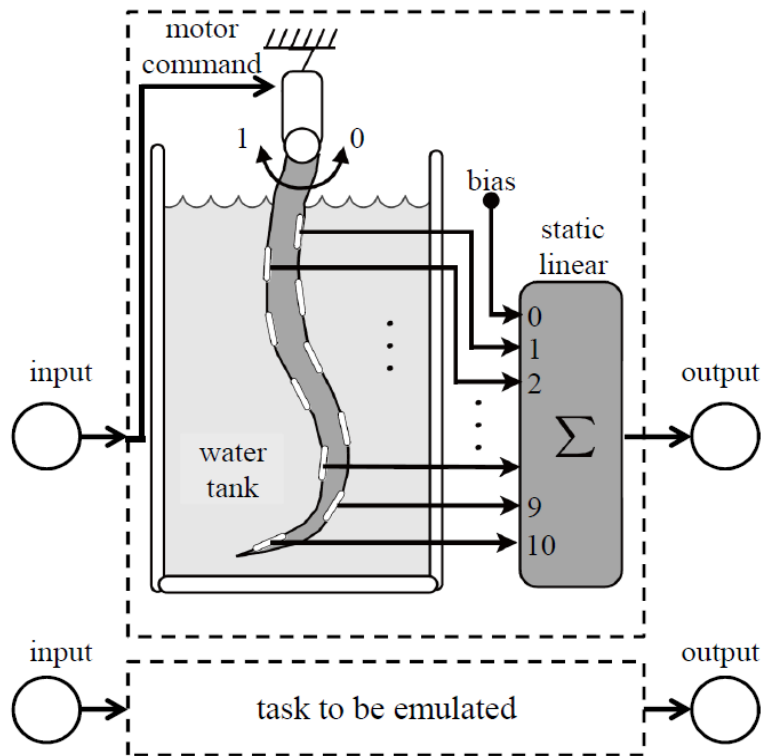
Physical platform



Experimental setting



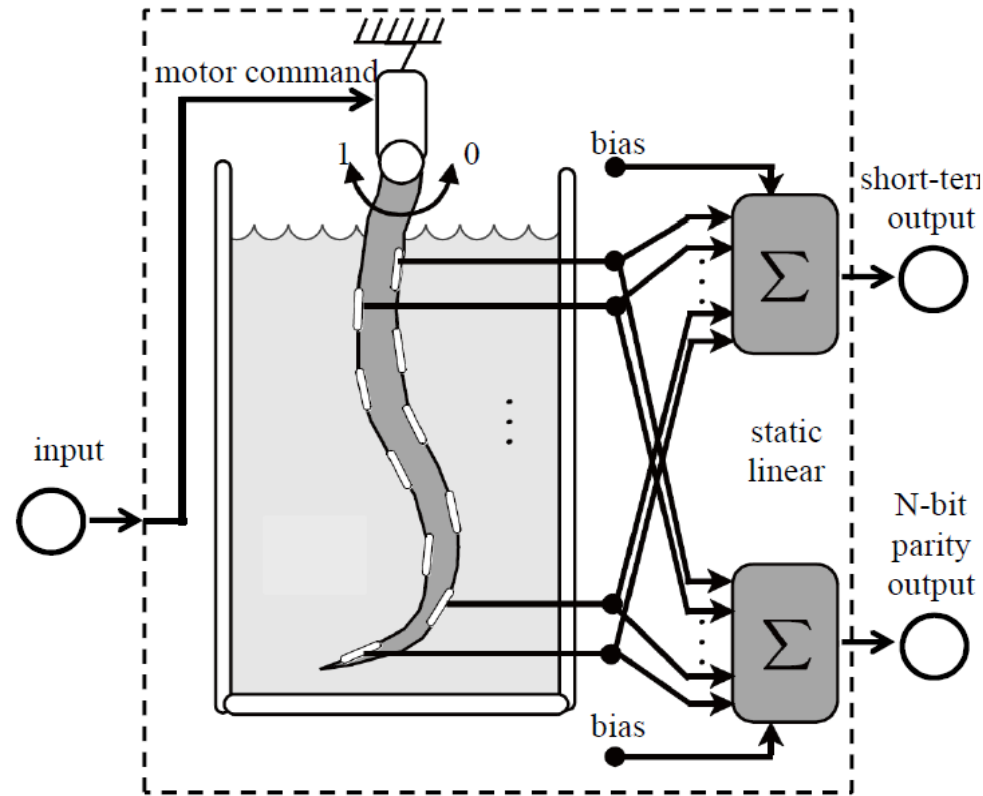
(Computational scheme)



Can reveal the expressive power “ f ” of physical dynamics!

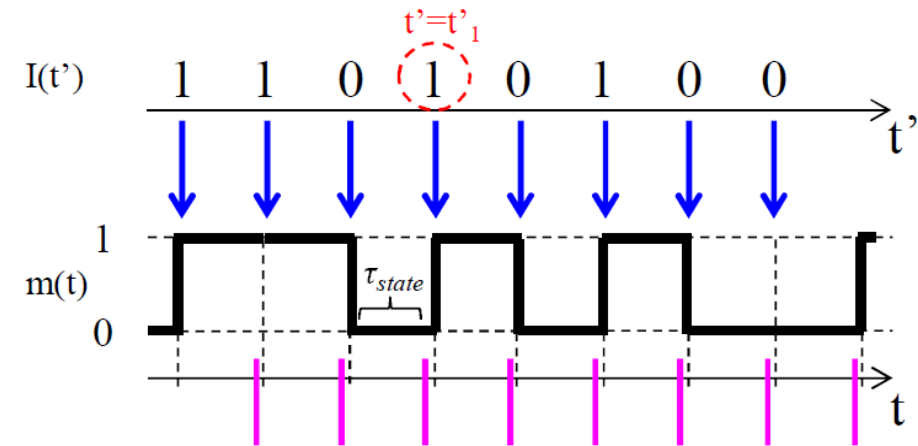
Evaluate the computational power of the arm

Open-loop



(multitasking)

Boolean functions:

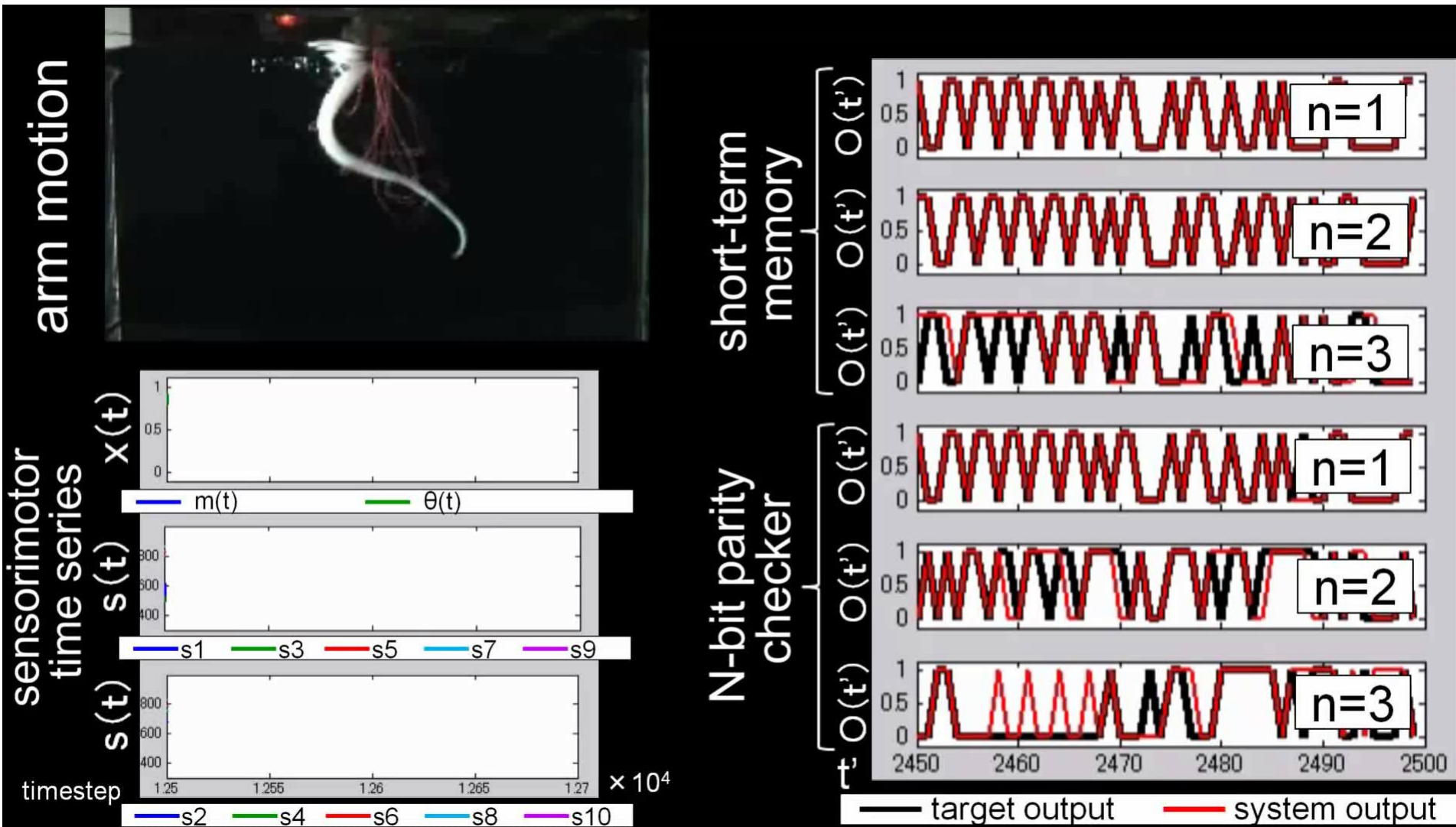


- Random binary input $I(t')$.
- A symbol t' takes τ_{state} timesteps.

K. Nakajima et. al., *J. R. Soc. Interface* 11: 20140437, 2014.

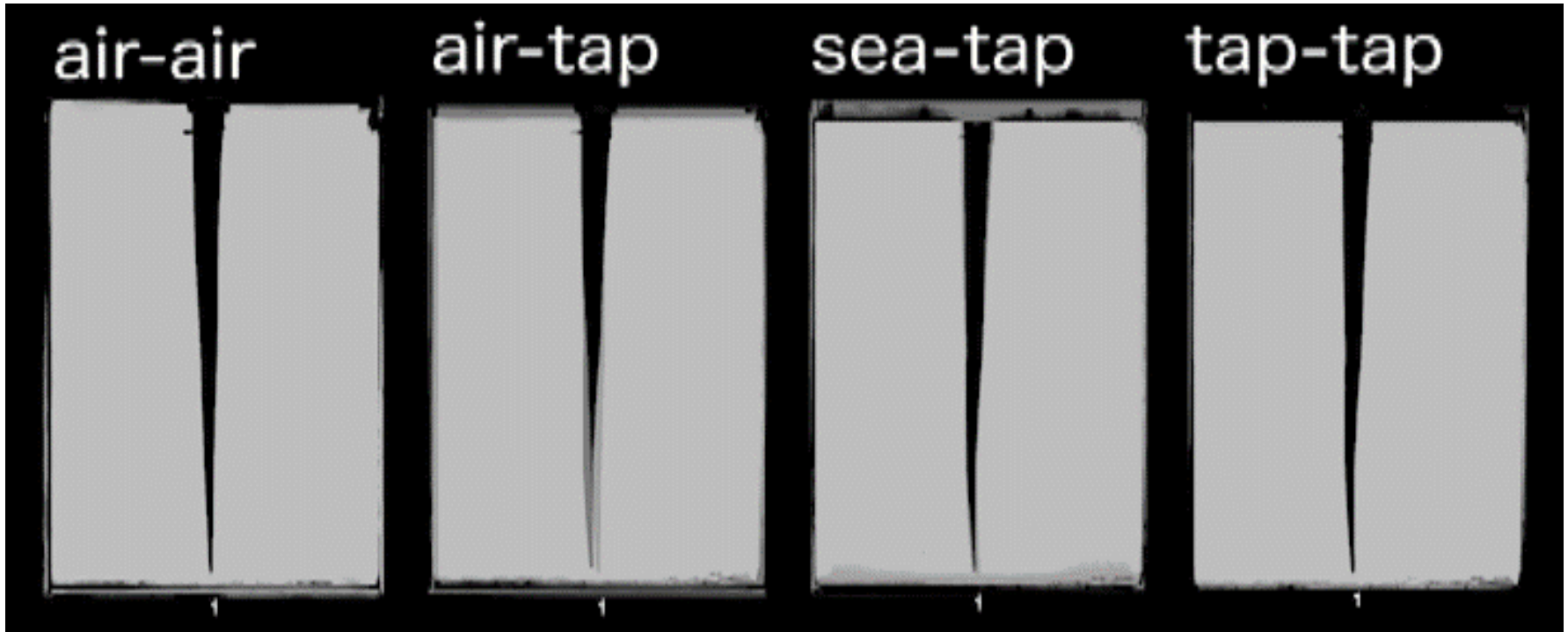
Implementing Boolean function emulation tasks!

Arm behavior with $\tau_{\text{state}}=5$



ESP in the octopus arm

K. Kagaya, B. Yu, Y. Minami, K. Nakajima, in *Proceedings of 2022 IEEE 5th International Conference on Soft Robotics (RoboSoft)*, pp. 224-230, 2022.



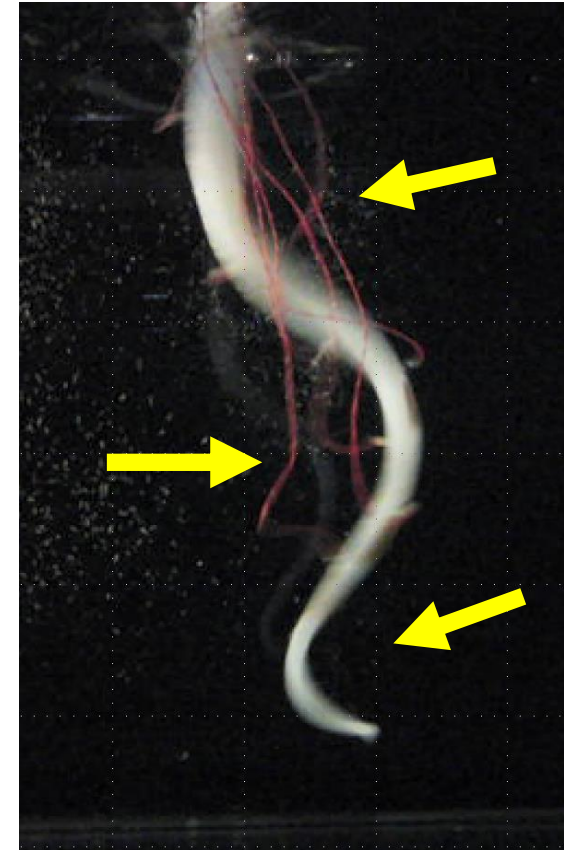
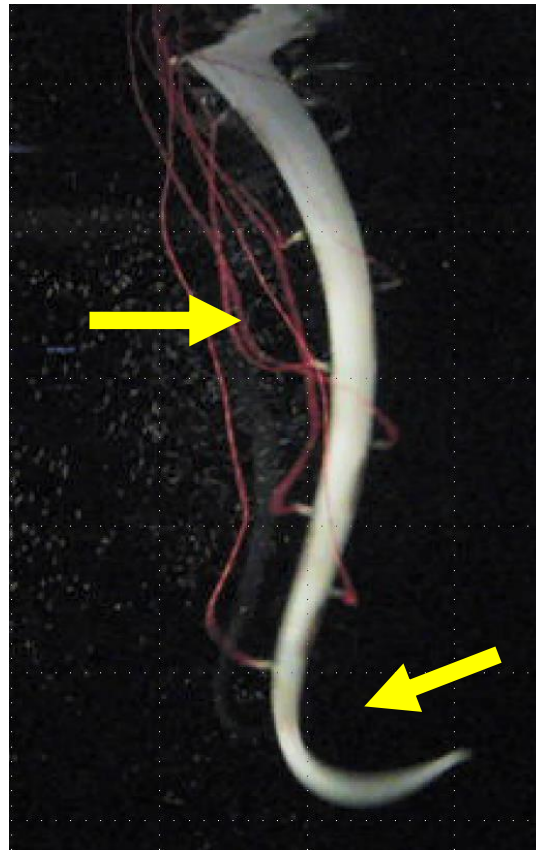
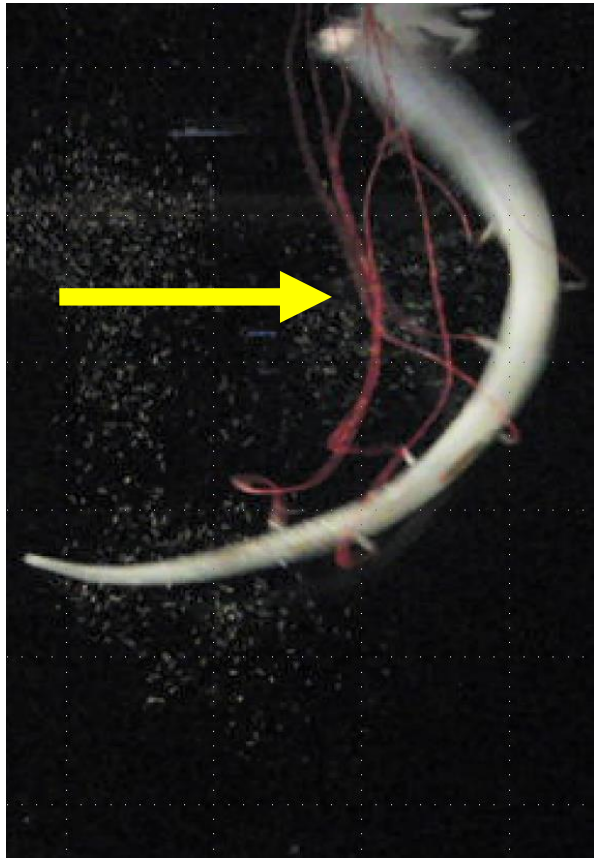
Injecting identical input series to different environmental conditions:

air, sea water, tap water

Common-signal-induced synchronization observed in the tap water condition but not in the air condition!

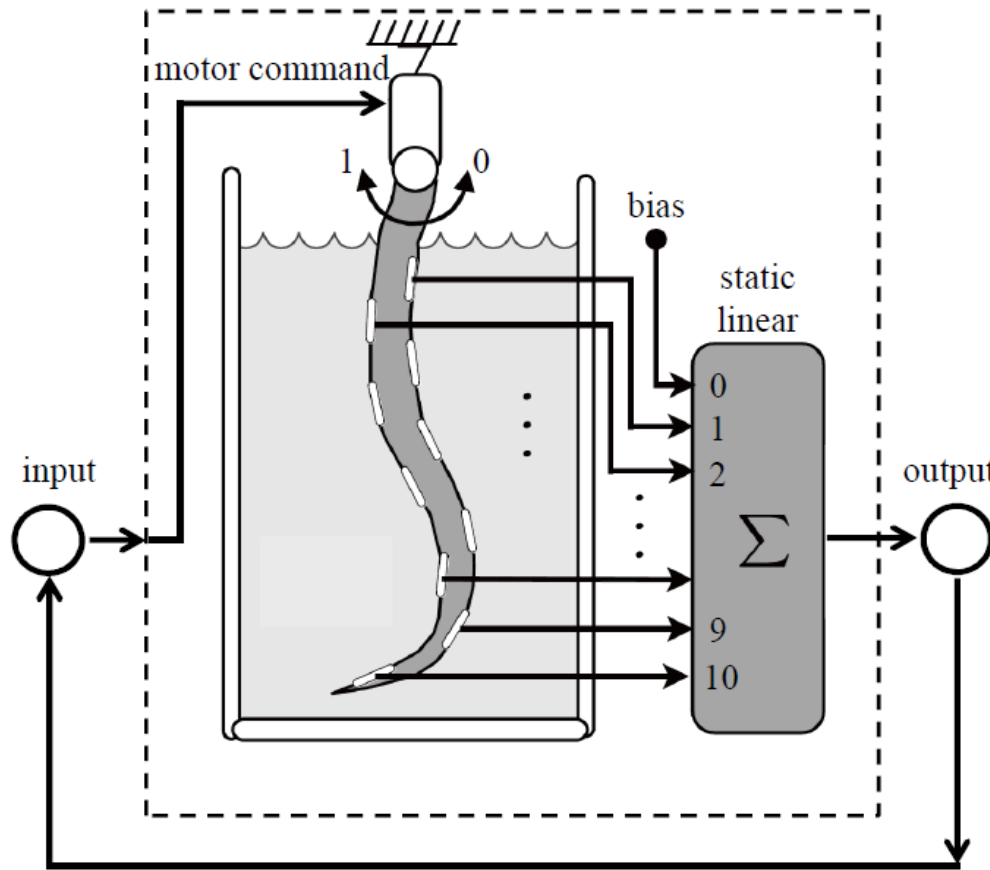
How does octopus arm store memory?

Only from current arm's shape, infer previous inputs!



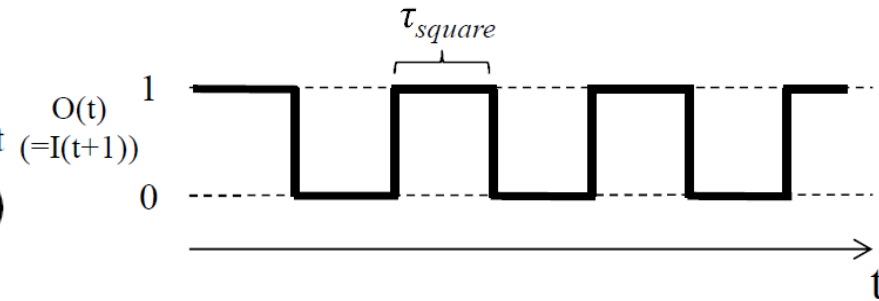
- Can infer previous inputs from arm's shape!
- **Rigid stick does not have this property!**

Closed-loop control: embedding motor program into the body



(Oscillatory pattern)

$$x(t) = \frac{1}{2}(\text{sgn}(\sin(\frac{2\pi}{\tau_{\text{square}}}t)) + 1)$$



Similar motor command with
octopus swimming robot!

- No addition of memory from external controller!
- Autonomous behavior control by closing the loop!
- Investigate its robustness!

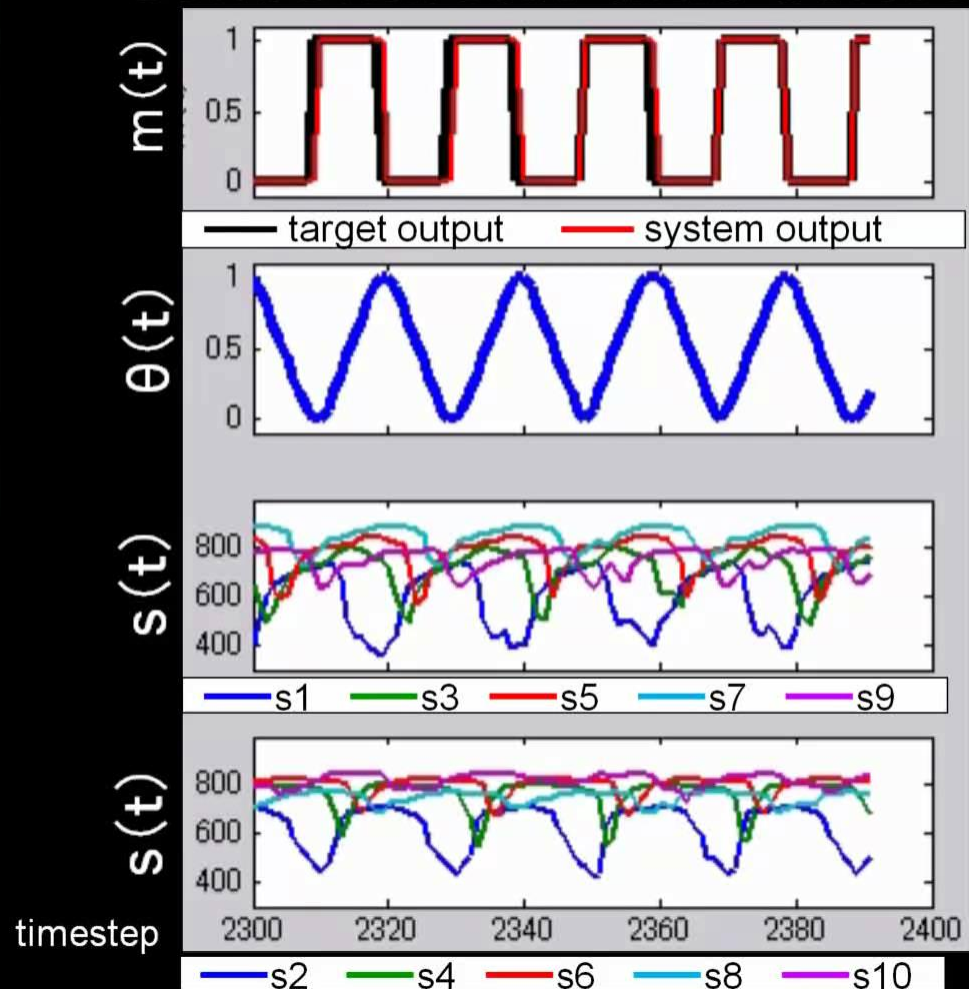
Closed loop control with $\tau_{\text{square}} = 10$ (manual perturbation)



arm motion

$\tau_{\text{square}} = 10$

sensorimotor time series



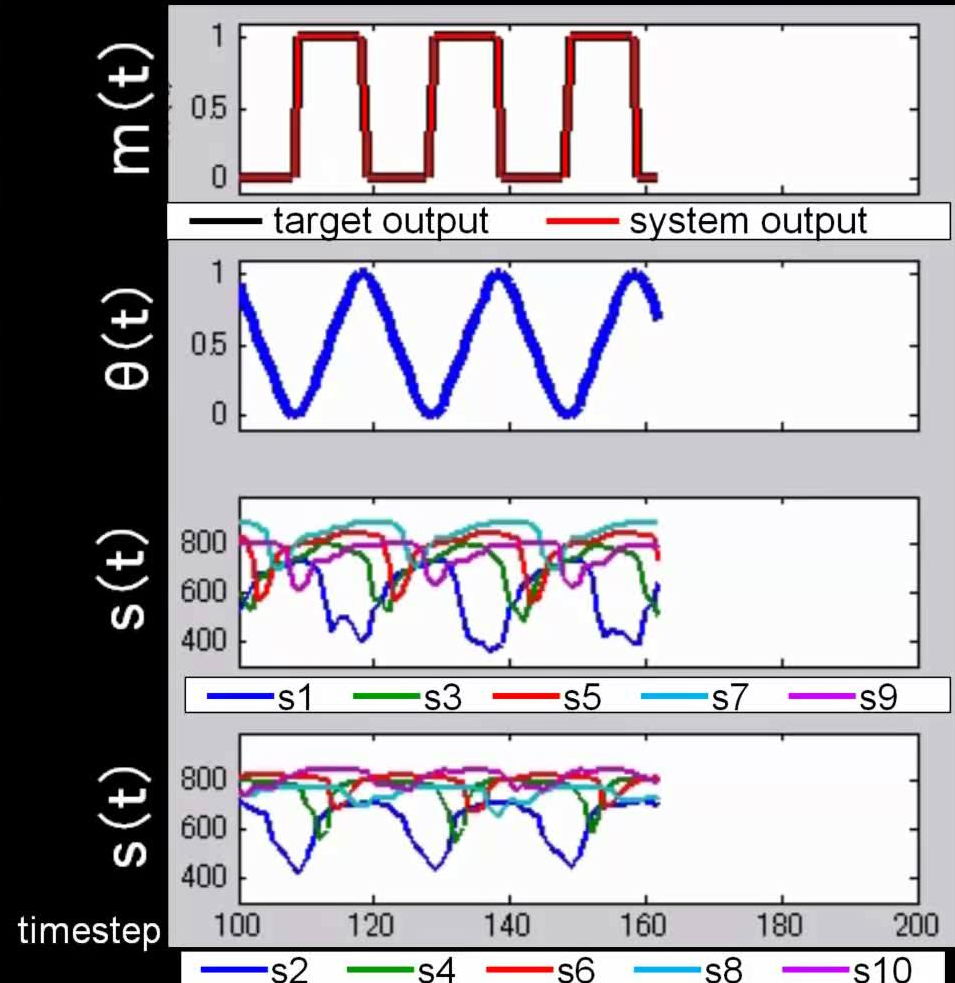
Closed loop control with $\tau_{\text{square}} = 10$



arm motion

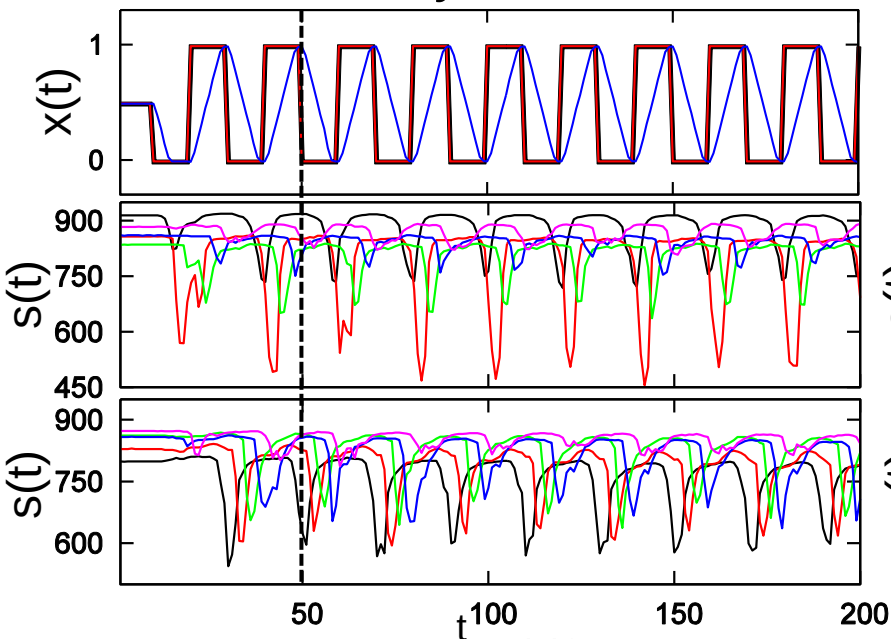
$\tau_{\text{square}} = 10$

sensorimotor time series

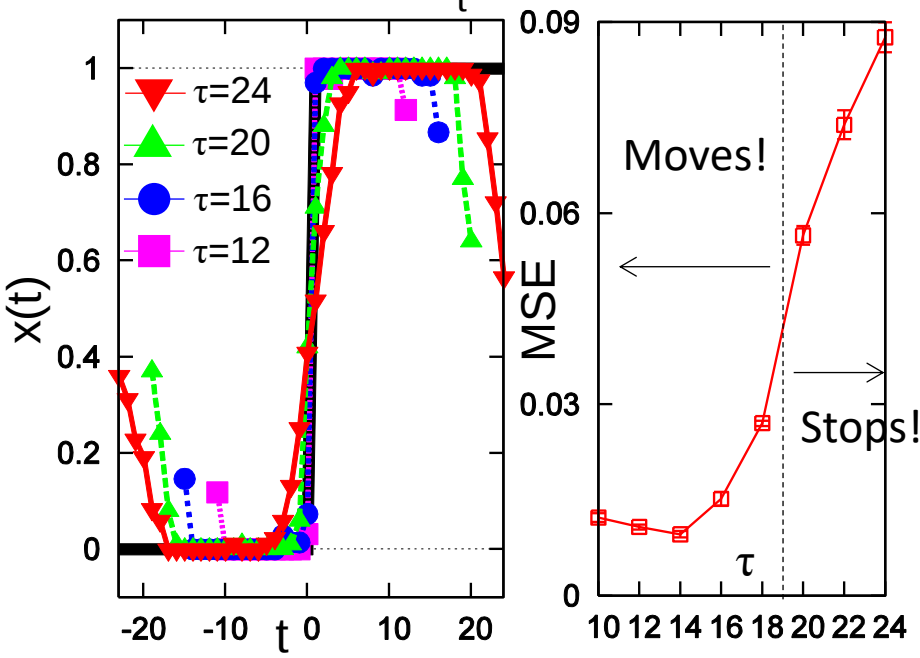
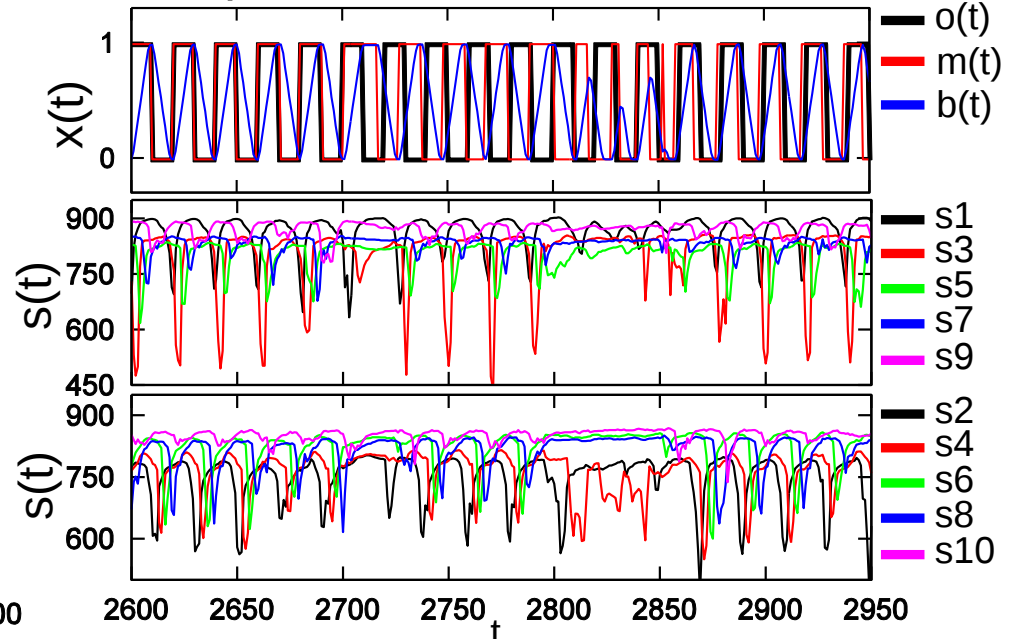


Closed-loop control: analysis

Motor and sensory time series



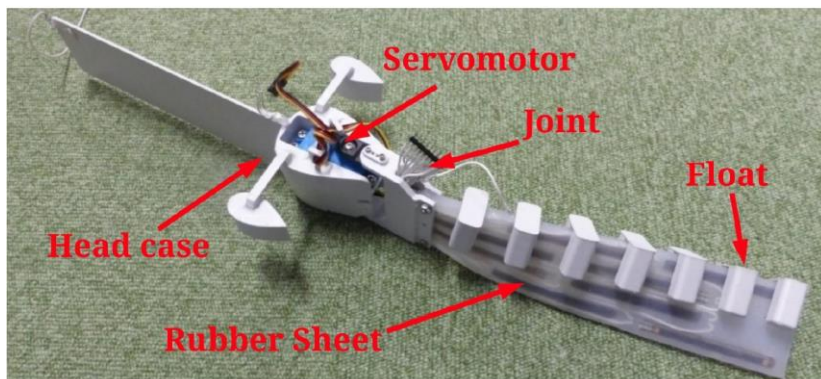
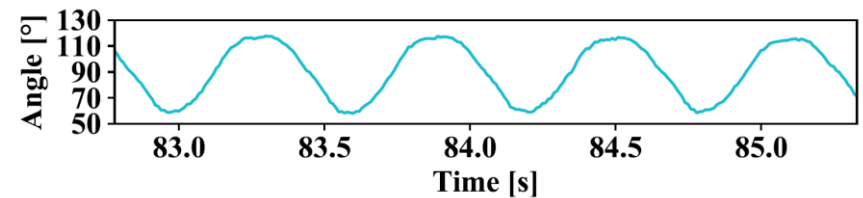
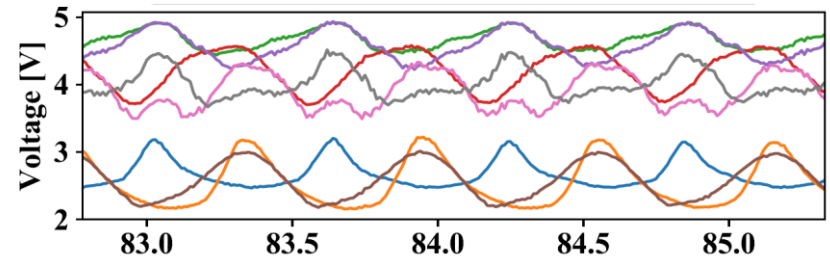
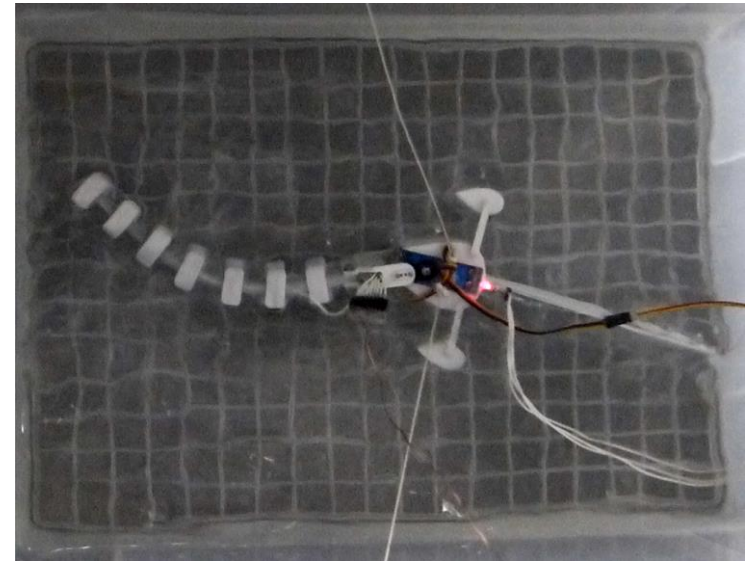
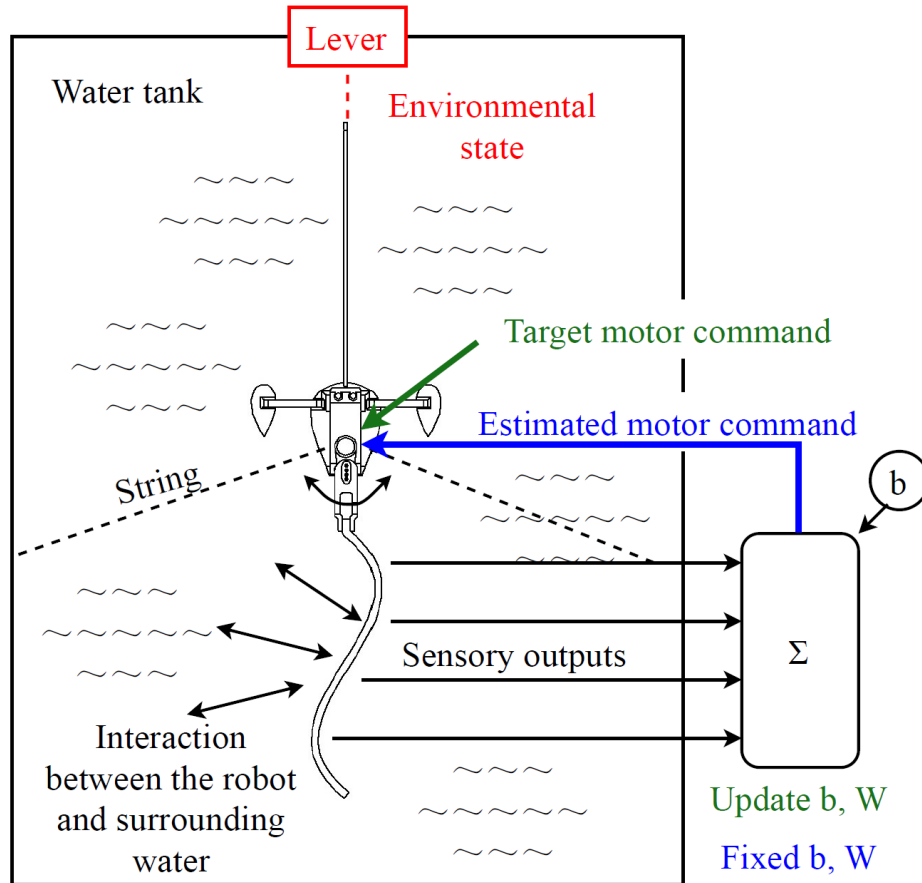
with perturbations



- Can embed closed-loop control!
- When τ gets long, memory disappears!
- Robust against external noise!

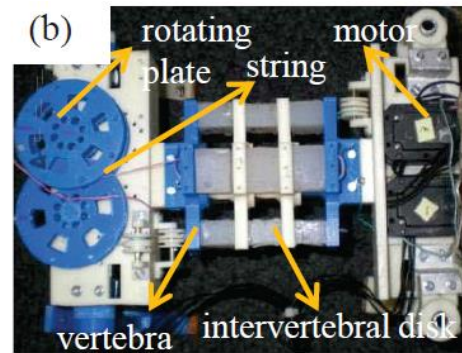
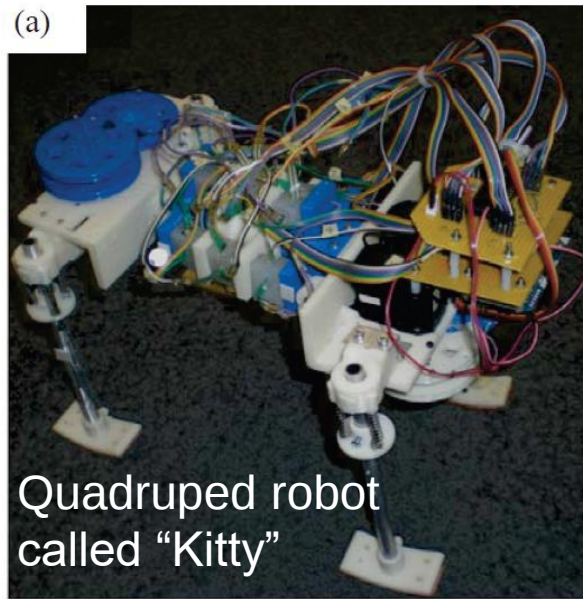
Fish robot based on PRC

Y. Horii et. al, in *Proceedings of the ALIFE 2021: The 2021 Conference on Artificial Life*, pp.92 (9pages), 2021.

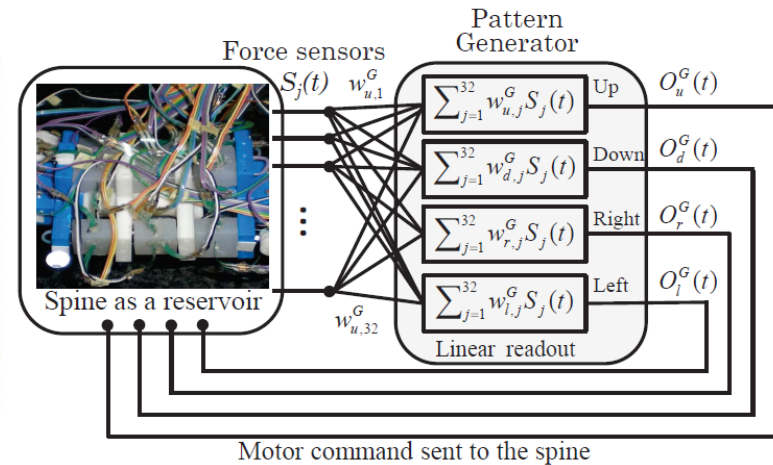


Closed-loop control can be successfully embedded!

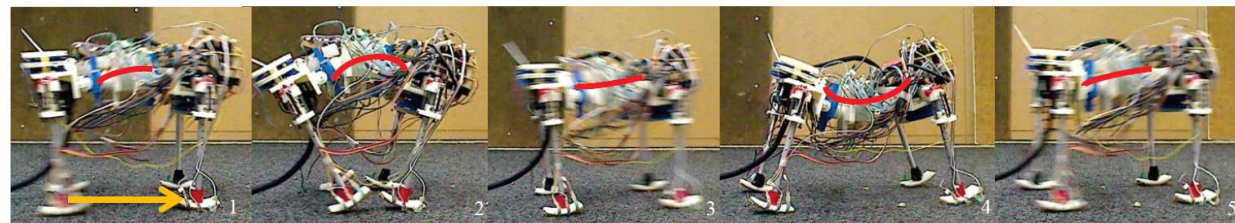
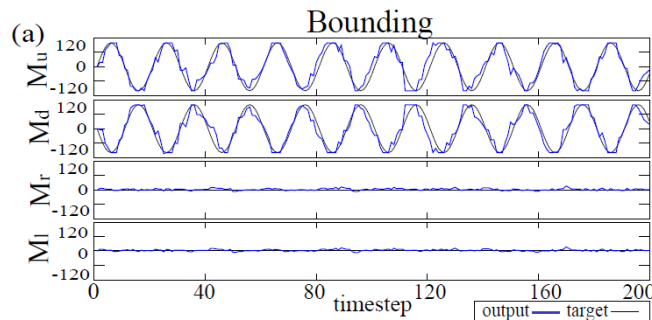
Closed-loop control for quadruped robot



Soft spinal structure



Demonstrating "Spinal Engine" hypothesis!

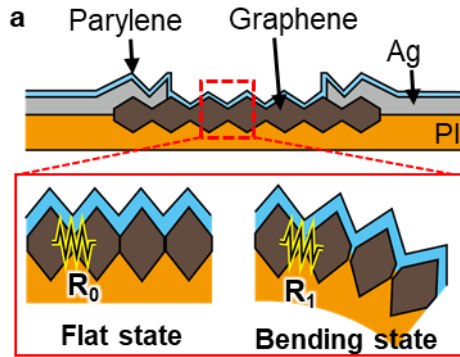


Q. Zhao et al., *Proceedings of 2013 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, pp. 1445-1451, 2013..

- Embedding multiple gait patterns (bounding, trotting, turning) in spine dynamics!
- No controller! Soft spinal dynamics are exploited to generate the motor pattern!

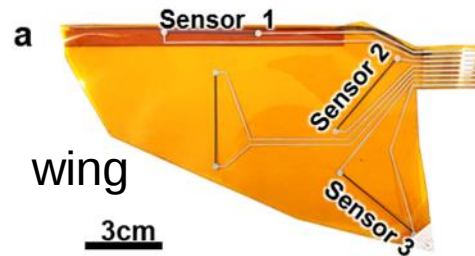
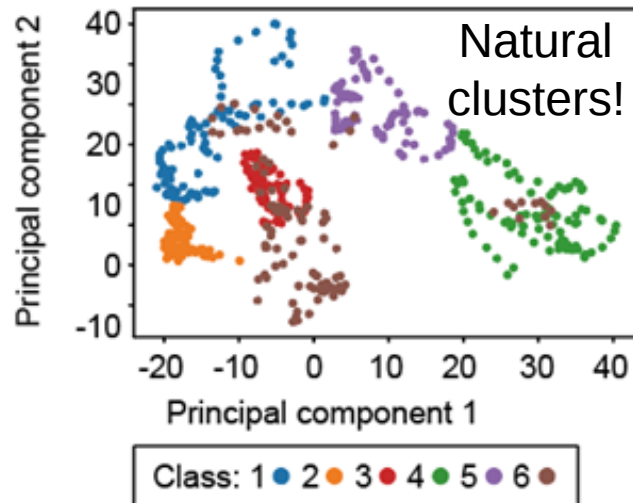
Wing as a reservoir

Tanaka, K., et. al. (2021). Flapping-Wing Dynamics as a Natural Detector of Wind Direction. *Advanced Intelligent Systems*, 3(2), 2000174.

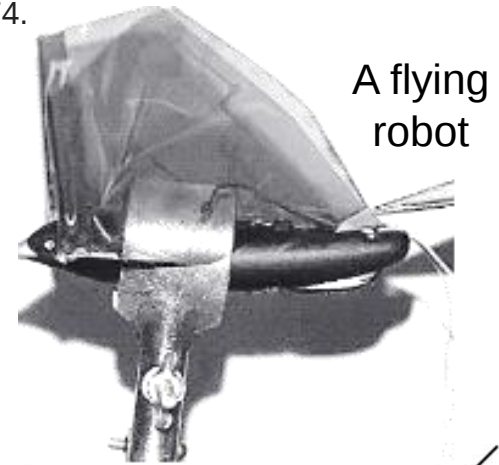


Embedding strain sensor
into the wing

(a) Principal component analysis

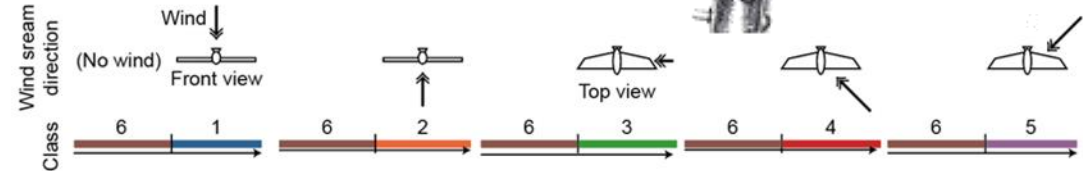


b

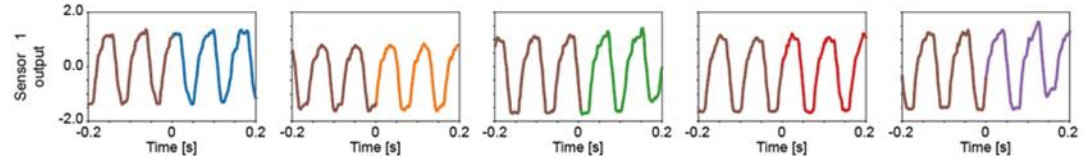


Typical classification results

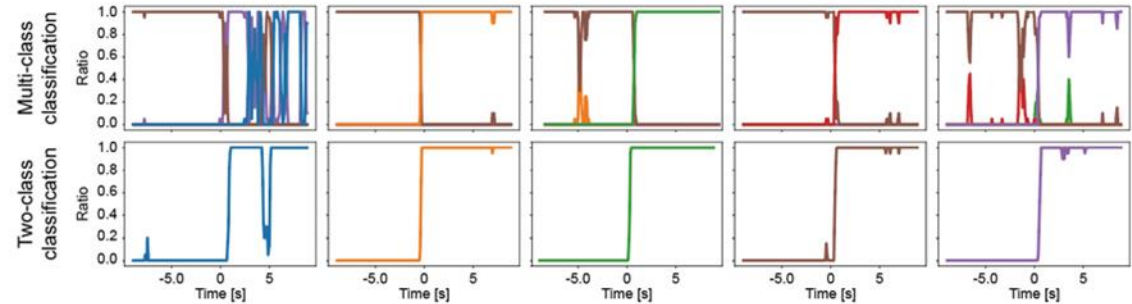
c



d



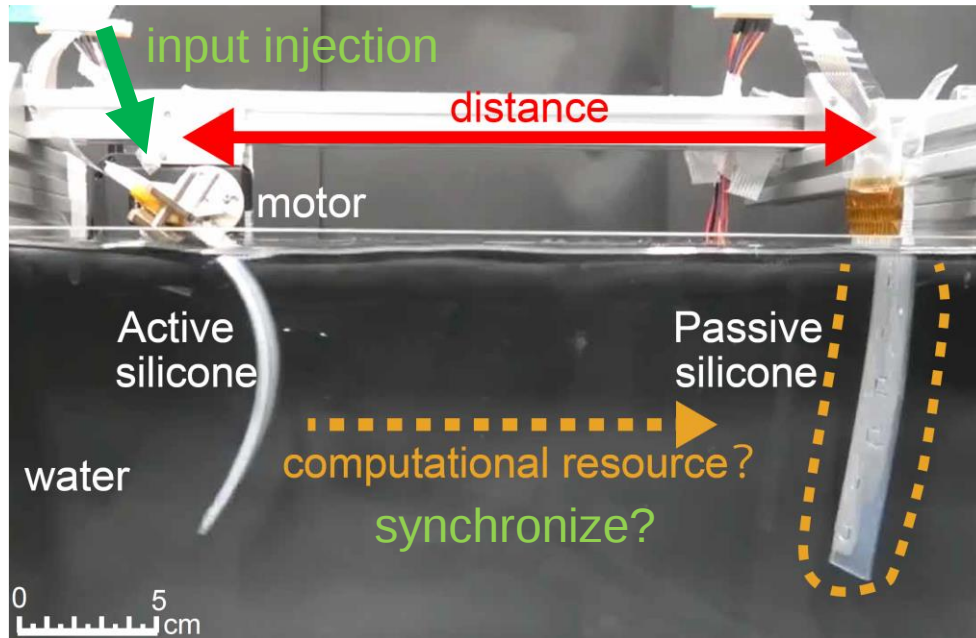
e



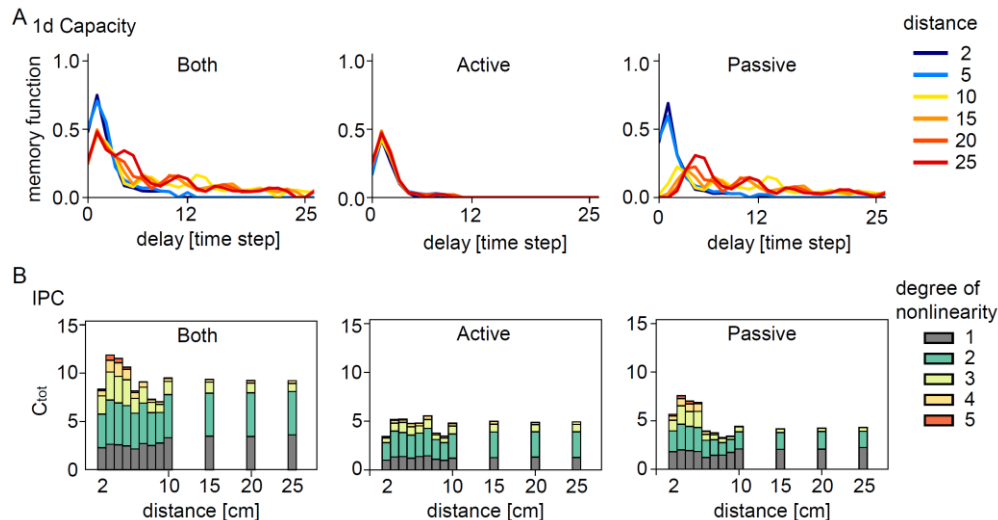
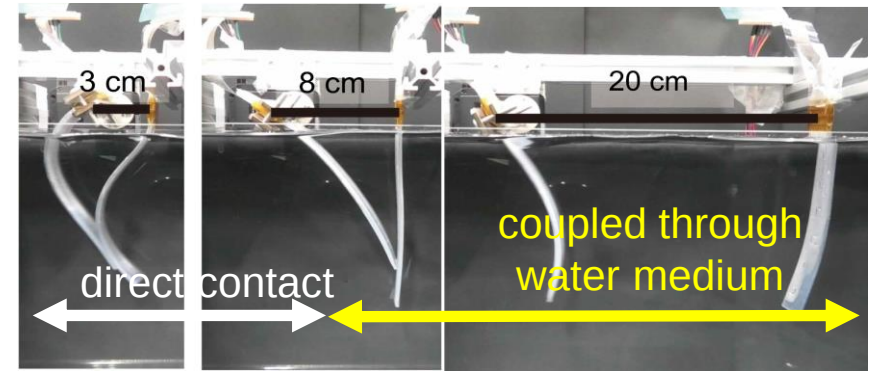
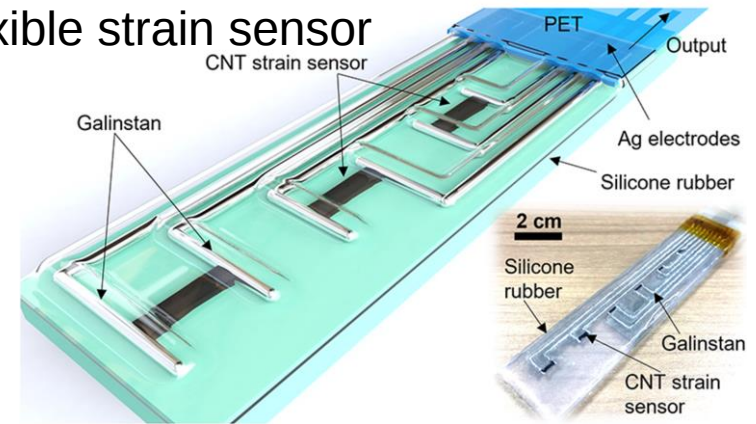
- Detecting wind direction with 0.915 accuracy!
- Wing dynamics as a natural classifier of wind direction!

Remote reservoirs

K. Tanaka, et. al., Adv. Intell. Syst. 2100166, 2022.



Flexible strain sensor



T. Kubota, et. al., Phys. Rev. Res. 3: 043135, 2021.

- Physical objects in spatially distance place can be used as a reservoir!
- Generalized synchronization induces self-organized *remote reservoirs*! (extending body)
- Interaction modality changes the computational capability!

Statement:

“By incorporating soft materials, the body can be used as a computational device!”

- Distributed computation – open-loop
- Embedding motor program into the body – closed-loop

Body structure of robots (animals) is not “random” but has specific morphology.

→ **Explore “why” from computational perspectives!**

Emulating oscillators



Experiment 2

Closed-loop attractor embedding

Akashi, N., Kuniyoshi, Y., Jo, T., Nishida, M., Sakurai, R., Wakao, Y., & Nakajima, K. (2024). Embedding bifurcations into pneumatic artificial muscle. *Advanced Science*, 2304402.

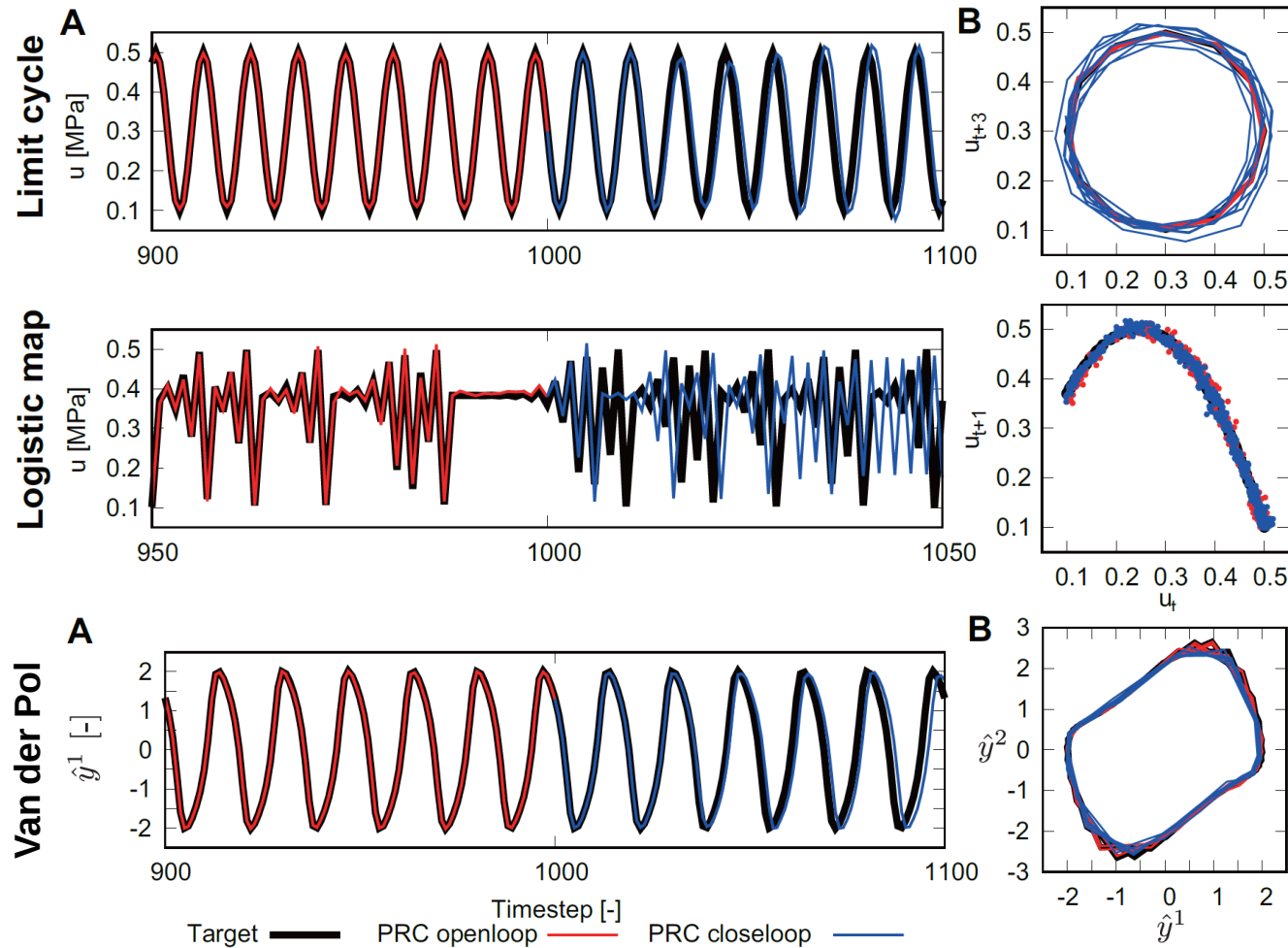
Emulating chaos



Chaotic attractor embedding

Akashi, N., Kuniyoshi, Y., Jo, T., Nishida, M., Sakurai, R., Wakao, Y., & Nakajima, K. (2024). Embedding bifurcations into pneumatic artificial muscle. *Advanced Science*, 2304402.

No need to run oscillators in the computer



$$y_n = \sin(an)$$

$$y_{n+1} = 3.7y_n(1 - y_n)$$

$$\begin{cases} \dot{x}_1 = x_2, \\ \dot{x}_2 = -x_1 + (1 - x_1^2)x_2 \end{cases}$$

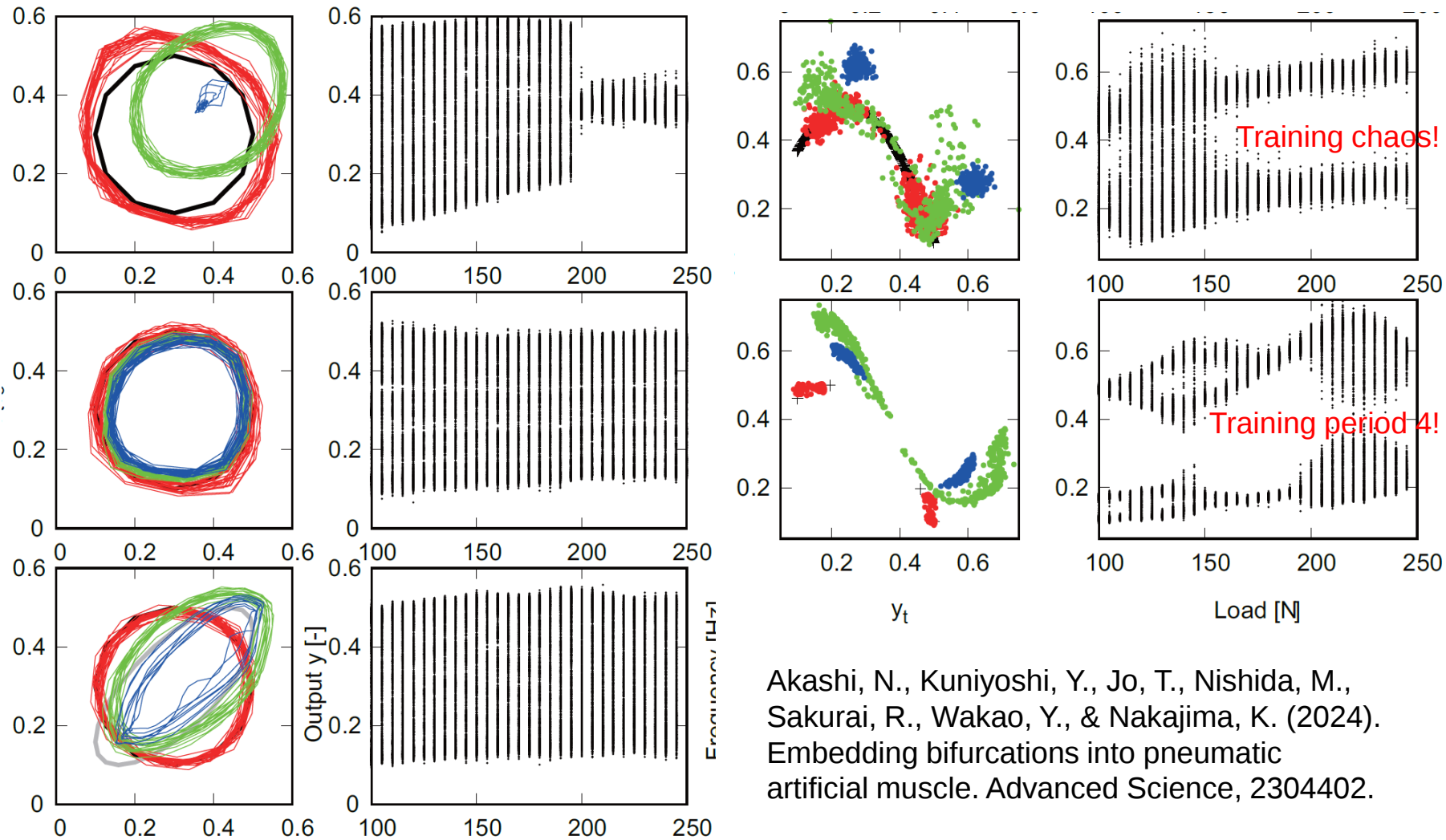
Akashi, N., Kuniyoshi, Y., Jo, T., Nishida, M., Sakurai, R., Wakao, Y., & Nakajima, K. (2024). Embedding bifurcations into pneumatic artificial muscle. *Advanced Science*, 2304402.

Embedding bifurcation

Experiment 4: Closed-loop bifurcation embedding

Akashi, N., Kuniyoshi, Y., Jo, T., Nishida, M., Sakurai, R., Wakao, Y., & Nakajima, K. (2024). Embedding bifurcations into pneumatic artificial muscle. *Advanced Science*, 2304402.

Embedding multiple attractors

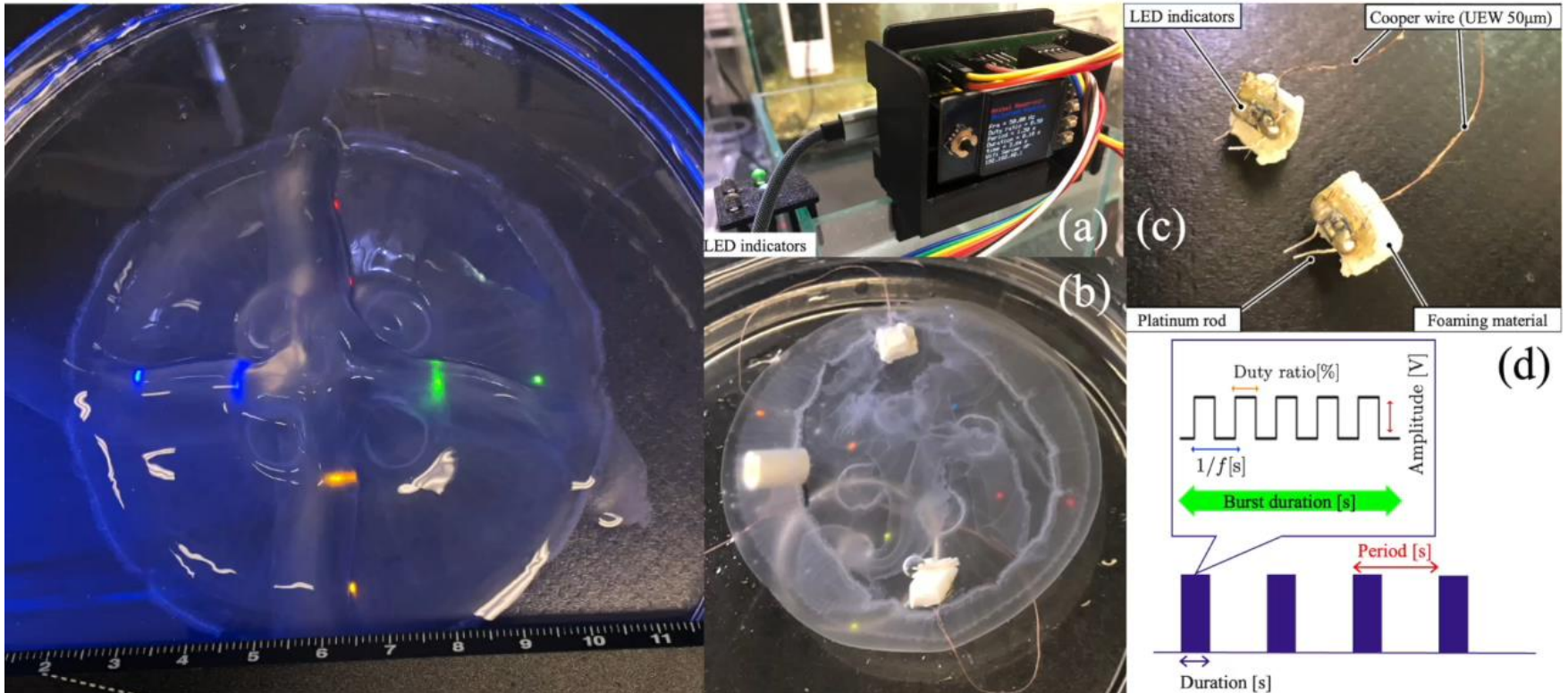


Akashi, N., Kuniyoshi, Y., Jo, T., Nishida, M., Sakurai, R., Wakao, Y., & Nakajima, K. (2024). Embedding bifurcations into pneumatic artificial muscle. *Advanced Science*, 2304402.

- Multiple untrained attractors can be obtained only by presenting a few attractors through underlying bifurcation!

Jellyfish cyborgs have been released...

VIE Tags & Electrical Stimulation



Owaki, D., Austin, M., Ikeda, S., Okuizumi, K., & Nakajima, K. (2024). A Jellyfish Cyborg: Exploiting Natural Embodied Intelligence as Soft Robots. *arXiv preprint arXiv:2408.01941*.

Thank you!