Spiking Control Systems

Reconciling physics and algorithmics ?

Rodolphe Sepulchre

"Jacques Morgenstern" Colloquium

Nice, October 2024

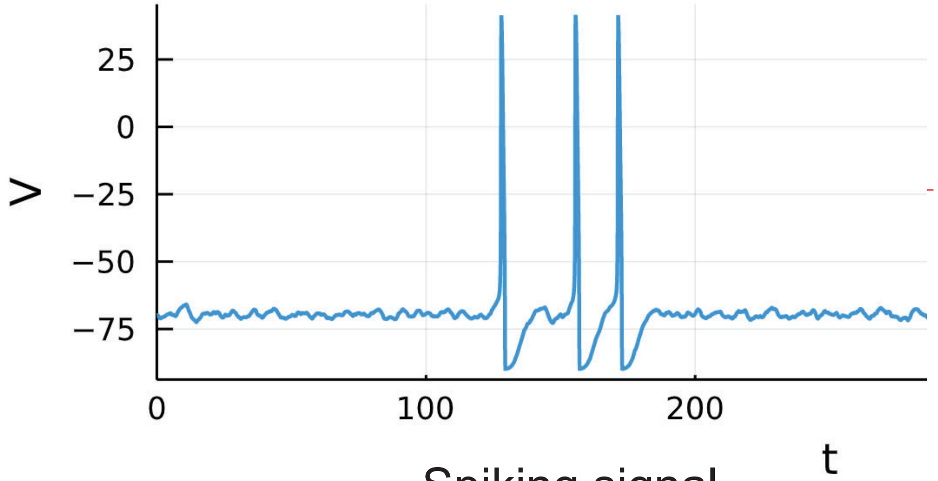
KU LEUVEN

UNIVERSITY OF CAMBRIDGE

Spiking intelligence

Bit stream

Substrate of machine intelligence



Spiking signal

Substrate of animal intelligence

Does it matter ?

Spiking Control Systems, IEEE Proceedings, RS, 2021

Spiking technology

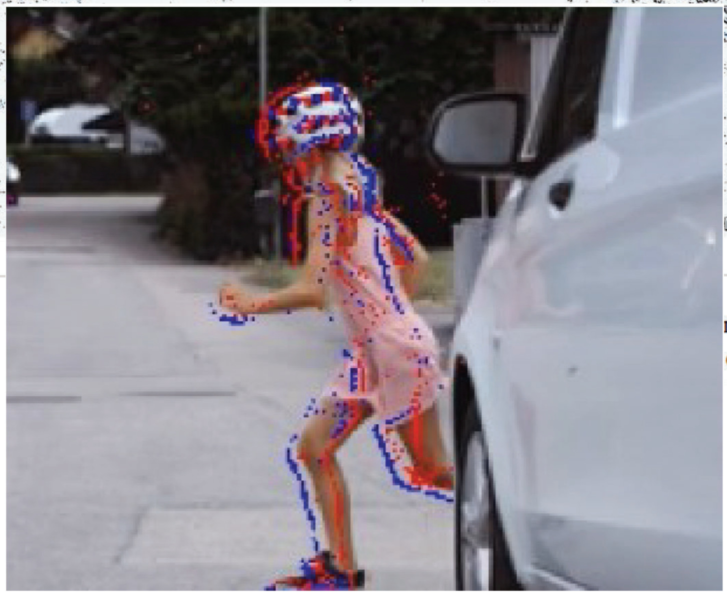
The Economist | Menu | Weekly edition | Search

Science & technology

Photography

A new type of camera

It could prove invaluable for robots, drones and driverless cars



Jan 26th 2022

ng medium to preserve an
over the years from plates

Gehrig, Scaramuzza, Low Latency Automotive Vision with Event Cameras, Nature, 2024

The Evolution of Event Cameras

2008 — First event camera by University of Zurich

Resolution: **128×128 pxl**
Pixel size: **40 microns**

2018 — ATIS-Gen3 by Prophesee

Resolution: **640×480 pxl**
Pixel size: **15 microns**

2019 — **United States Patent**

EVENT CAMERA FOR GENERATION OF EVENT-BASED IMAGES
Applicant: **Facebook Technologies**, LLC, Menlo Park, CA (US)

METHOD AND DEVICE FOR EYE TRACKING USING EVENT CAMERA DATA
Applicant: **Apple Inc.**, Cupertino, CA (US)

2021 — SONY, SAMSUNG, OmniVision

First Full-HD event sensors:

Resolution: **1280×720 pxl**
Pixel size: **5 microns**

2022 — Meta

Meta opens Event-based Sensing Lab

First event cameras in space

2023


REUTERS

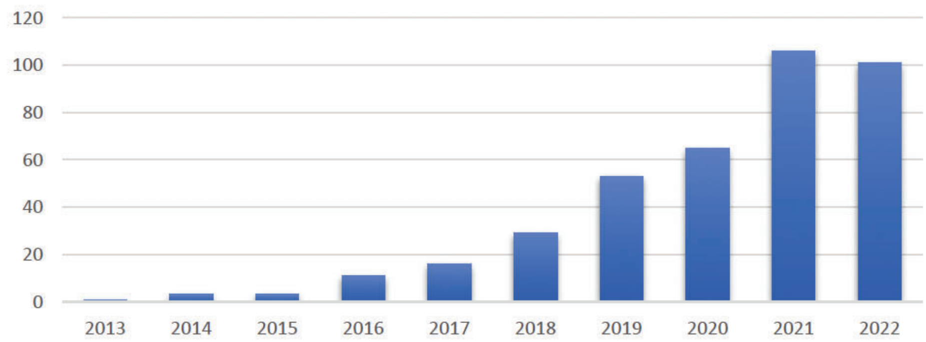
Camera chip startup Prophesee and Qualcomm sign multi-year deal

By Jane Lee

February 27, 2023

PROPHESEE | Qualcomm

Event-camera Papers in Robotics and Computer Vision venues



Courtesy from D. Scaramuzza

Spiking Neural Networks

Perspective

Towards spike-based machine intelligence with neuromorphic computing

https://doi.org/10.1038/s41586-019-1677-2

Kaushik Roy[1]*, Akhilesh Jaiswal[1] & Priyadarshini Panda[1]

Received: 23 July 2018

Spiking Neural Networks: The next "Big Thing" in AI?

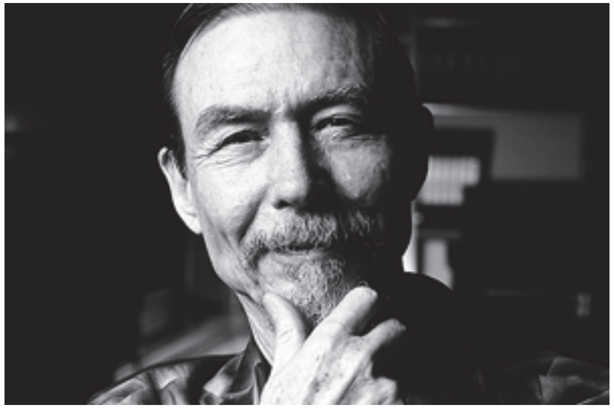
Dean S Horak · Follow

7 min read · Feb 22, 2024

"For the first time, we are seeing a quantitative picture emerge that validates this promise. Together, with our research partners, we plan to build on these insights to enable wide-ranging disruptive commercial applications for this nascent technology."

—Mike Davies
Director of Intel's Neuromorphic Computing Lab

An early prediction of the bottleneck of digital technology…



Neuromorphic Electronic Systems

CARVER MEAD

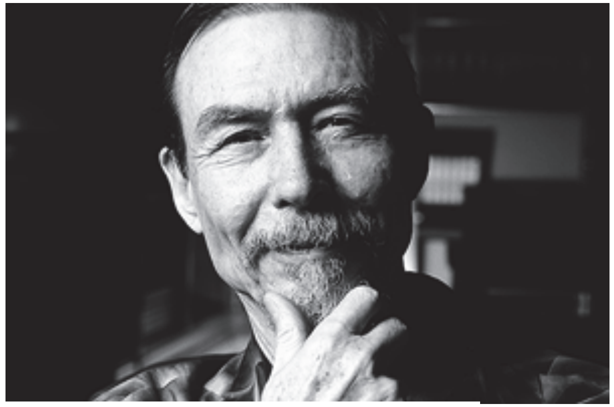
(IEEE Proceedings, 1990)

Invited Paper

Biological information-processing systems operate on completely different principles from those with which most engineers are familiar. For many problems, particularly those in which the input data are ill-conditioned and the computation can be specified in a relative manner, biological solutions are many orders of magnitude more effective than those we have been able to implement using digital methods. This advantage can be attributed principally to the use of elementary physical phenomena as computa-

does. We have e
cost of computa
not begin to do t
by the brains of i
performed by th
to the point whe
easy. Multiplyin

A radical proposal



Neuromorphic Electronic Systems

CARVER MEAD

Invited Paper

~~Clocks~~ Events

~~Bits~~ Spikes

technology: make the transistor a *mixed* device
(by exploiting its analog range)

Digital computation: a broken model ?

ENERGY

The Environmental Impact of ChatGPT: A Call for Sustainable Practices In AI Development

BY SOPHIE | GLOBAL COMMONS | APR 28TH 2023 | 4 MINS

Cybercrime To Cost The World $9.5 Trillion USD Annually In 2024

Cybersecurity Facts, Figures, Predictions and Statistics Sponsored by eSentire

– Steve Morgan, Editor-in-Chief

Sausalito, Calif. – Oct. 25, 2023 / Press Release

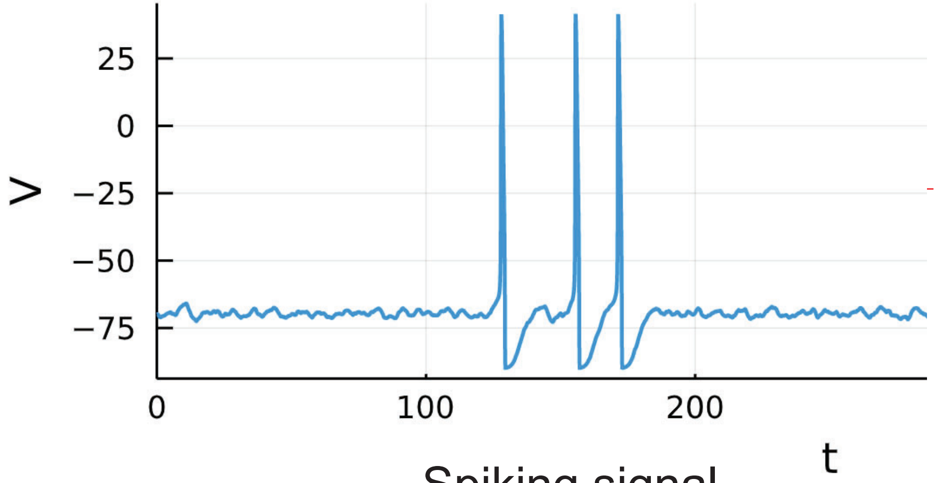
Cybercrime is predicted to cost the world $9.5 trillion USD in 2024, according to Cybersecurity Ventures. If it were measured as a country, then cybercrime would be the world's third largest economy after the U.S. and China. Download the Report

May 13, 2021
12:45 PM CEST
Last Updated a month ago

Factbox: How big is Bitcoin's carbon footprint?

Spiking intelligence: a control problem ?

Bit stream



Spiking signal

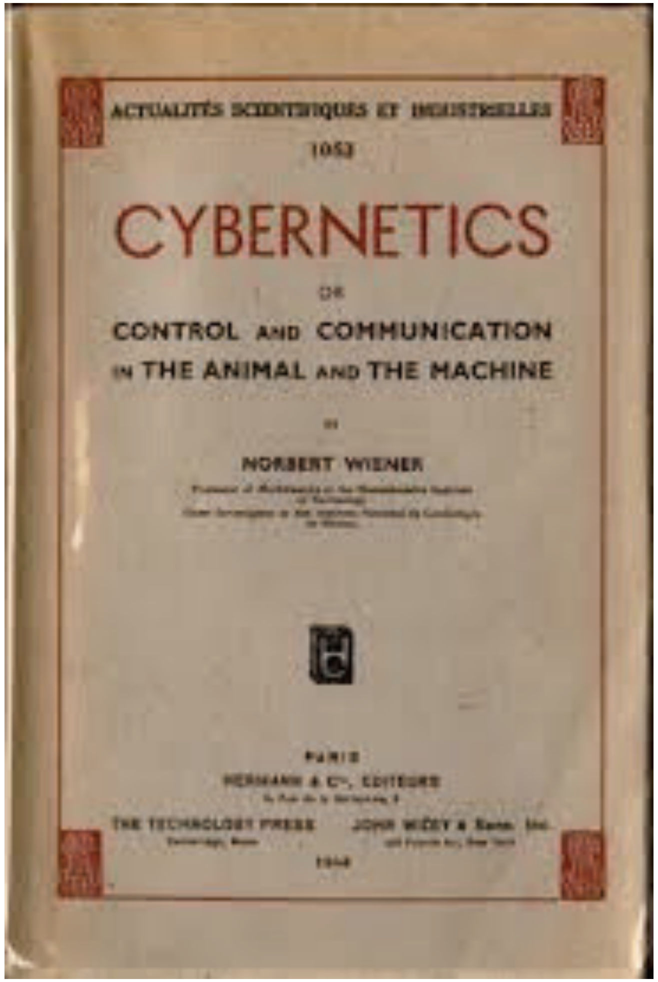
Substrate of machine intelligence

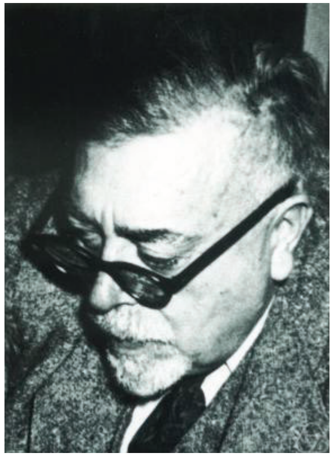
Substrate of animal intelligence

What makes it a *control* question ?

Spiking Control Systems, IEEE Proceedings, RS, 2021

Animal vs Machine Intelligence:
the central question of cybernetics





We have decided to call the entire field of control and communication theory, whether in the machine or in the animal, by the name *Cybernetics*, which we form from the Greek χυβερνήτης or *steersman*. In choosing this term, we wish to recognize that the first significant paper on feedback mechanisms is an article on governors, which was published by Clerk Maxwell in 1868, and that *governor* is derived from a Latin corruption of χυβερνήτης.[1]

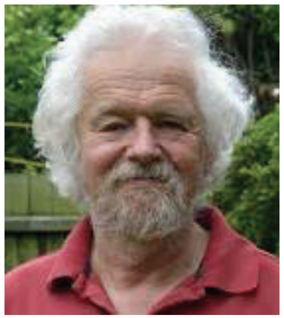
—NORBERT WIENER

Adaptation

Computation

A laptop computer resembles the human brain in volume and power use—but it is stupid. Deep Blue, the IBM supercomputer that crushed Grandmaster Garry Kasparov at chess, is 100,000 times larger and draws 100,000 times more power (figure I.1). Yet, despite Deep Blue's excellence at chess, it too is stupid, the electronic equivalent of an idiot savant. The computer operates at the speed of light whereas the brain is slow. So, wherein lies the brain's advantage?

Principles of Neural Design, Sterling & Laughlin, MIT Press, 2017



Do brains compute ? RS, TedX talk, 2014

Control system

From Wikipedia, the free encyclopedia

For other uses, see Control system (disambiguation).

A **control system** manages, commands, directs, or regulates the behavior of other devices or systems using control loops. It can range from a single home heating controller using a thermostat controlling a domestic boiler to large industrial control systems which are used for controlling processes or machines.

For continuously modulated control, a feedback controller is used to automatically control a process or operation. The control system compares the value or status of the process variable (PV) being controlled with the desired value or setpoint (SP), and applies the difference as a control signal to bring the process variable output of the plant to the same value as the setpoint.

For sequential and combinational logic, software logic, such as in a programmable logic controller, is used.

Choose your world: physics OR algorithmics

Different courses, different languages, distinct worlds …

The AI gap

Physics	***Algorithmics***
Physical	Computational
Embodied	Virtual
Continuous	Discrete
EE	CS
Odes	Automata
Signals	Data
Calculus	Logics
Circuits	Graphs
Pre-1950	Post-1950

Reconciling physics and algorithmics

Physics

continuous

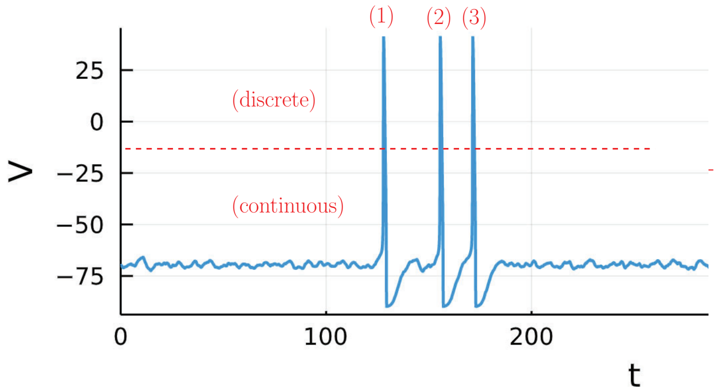
physical

regulation

adaptation

adaptive but unreliable

Neuromorphics



(a) The Dynamic Vision Sensor (DVS).

adaptive and reliable

Algorithmics

discrete

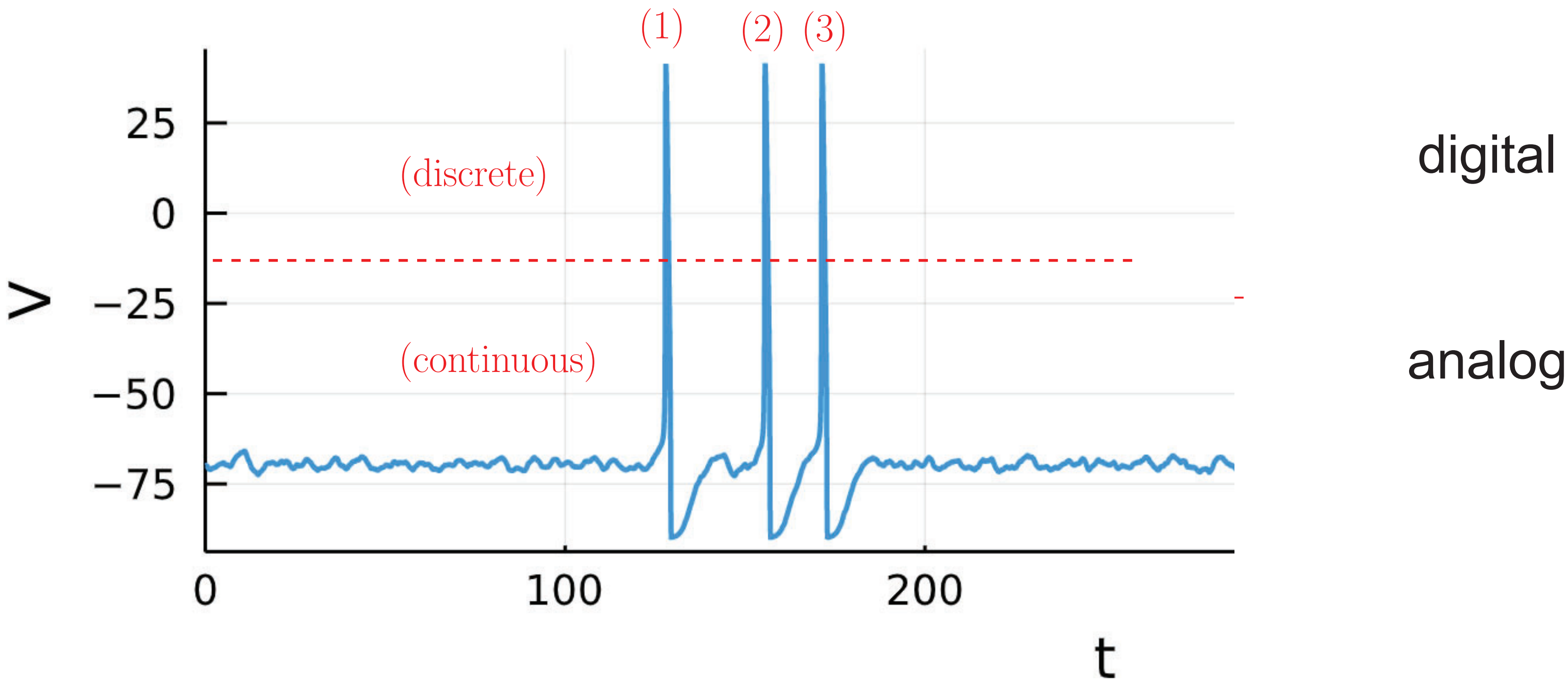
computational

automation

decision-making

reliable but inefficient

Spiking signals and systems



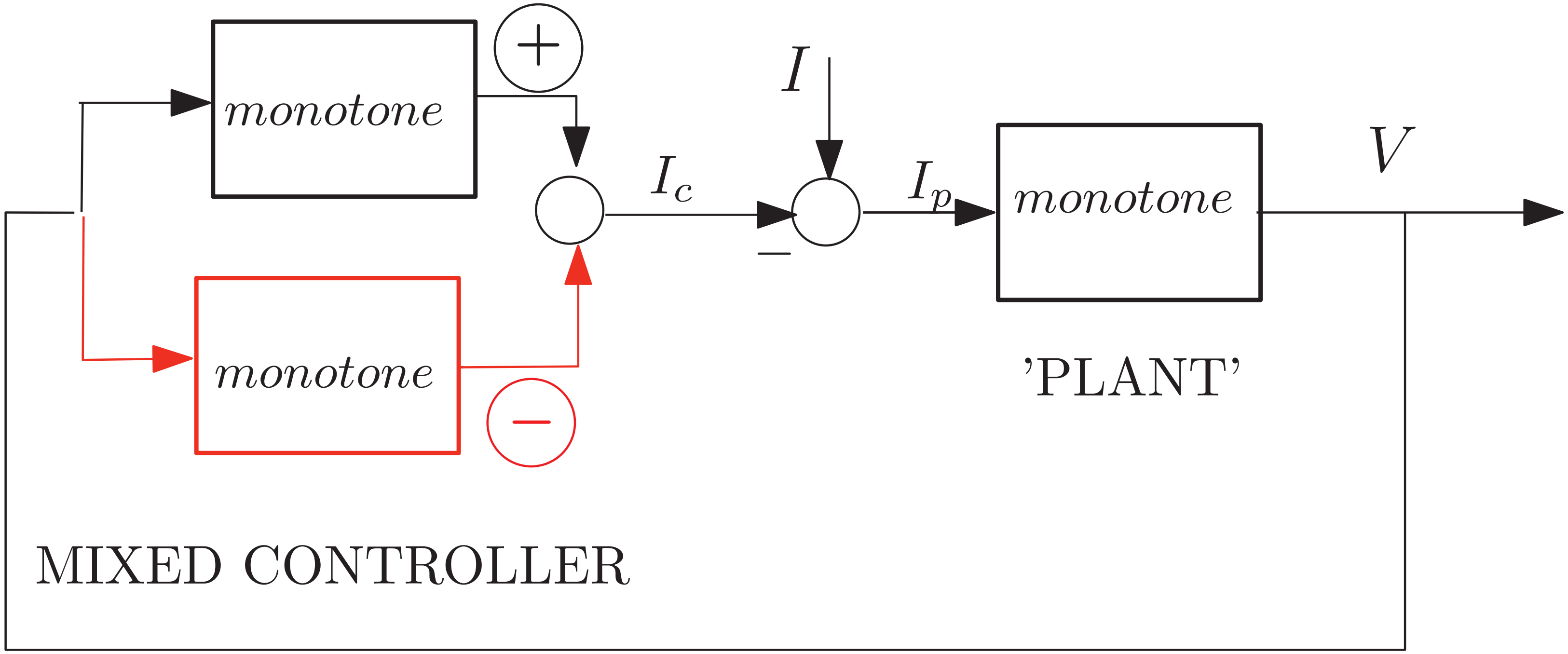
Do we have a theory for

computing / processing / controlling

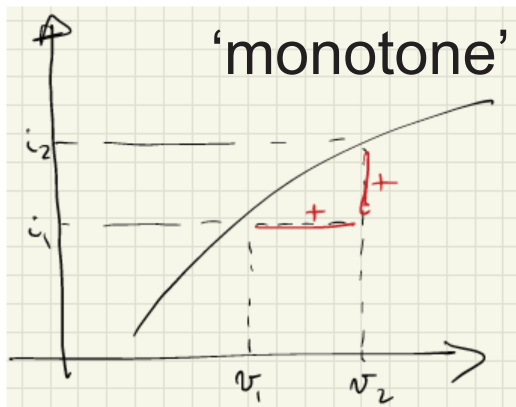
with *spiking* signals ?

IEEE Proceedings, 2022

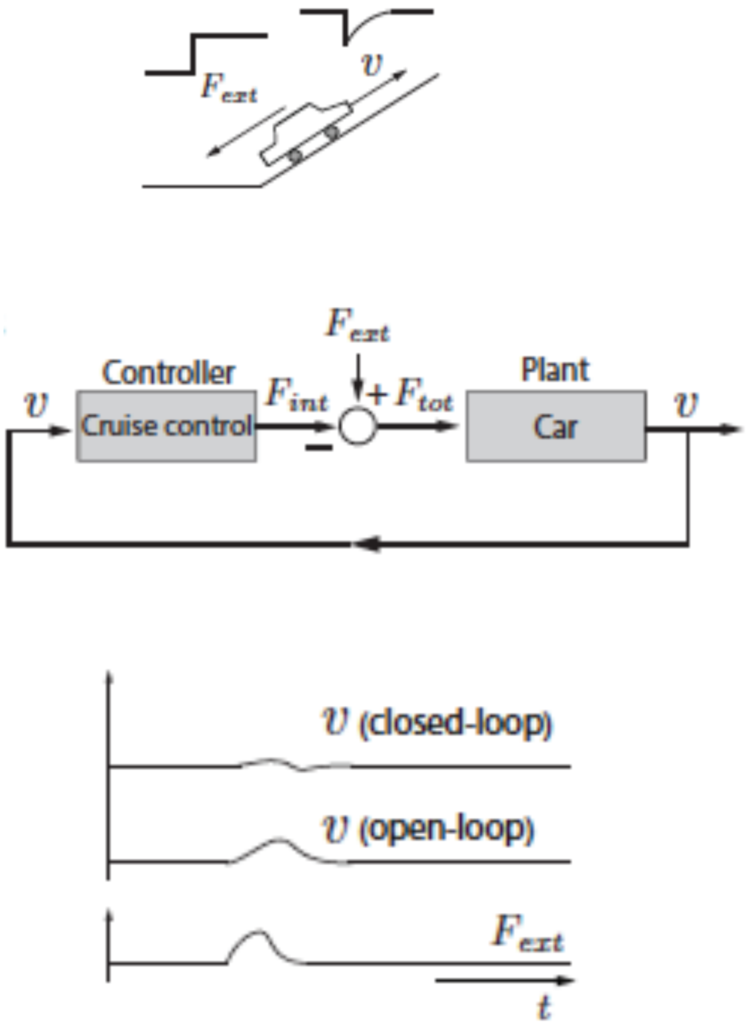
A mixed feedback principle



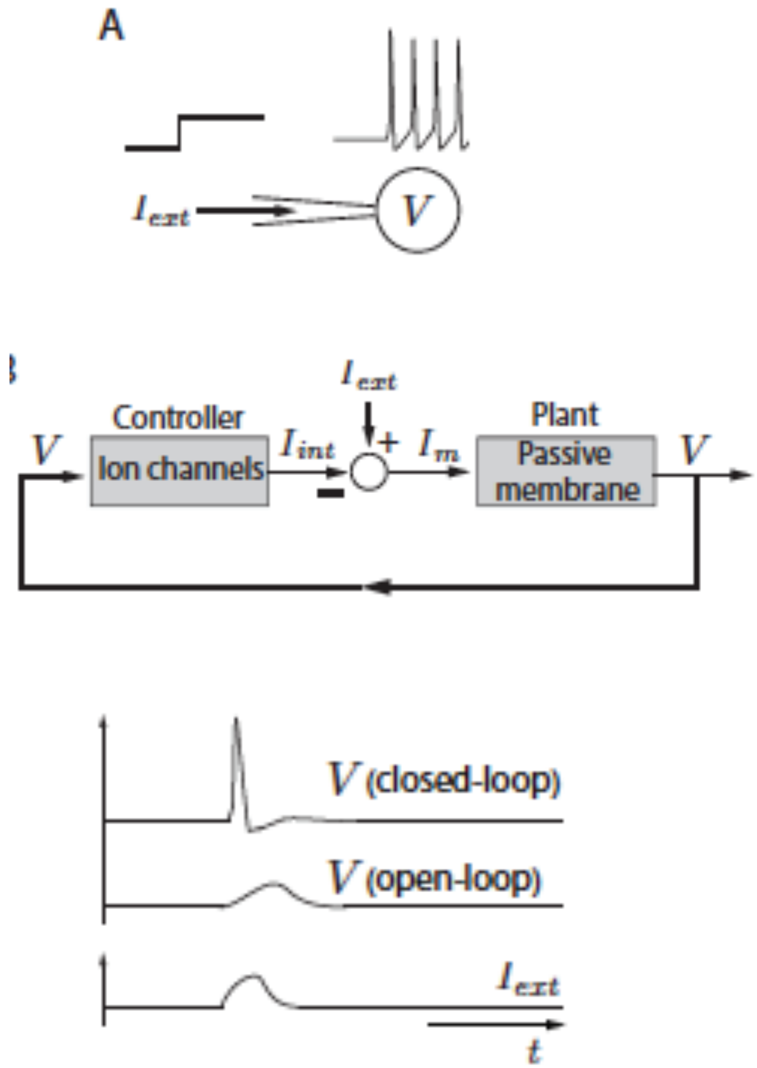
IEEE Proceedings, 2022



Classical control vs mixed control

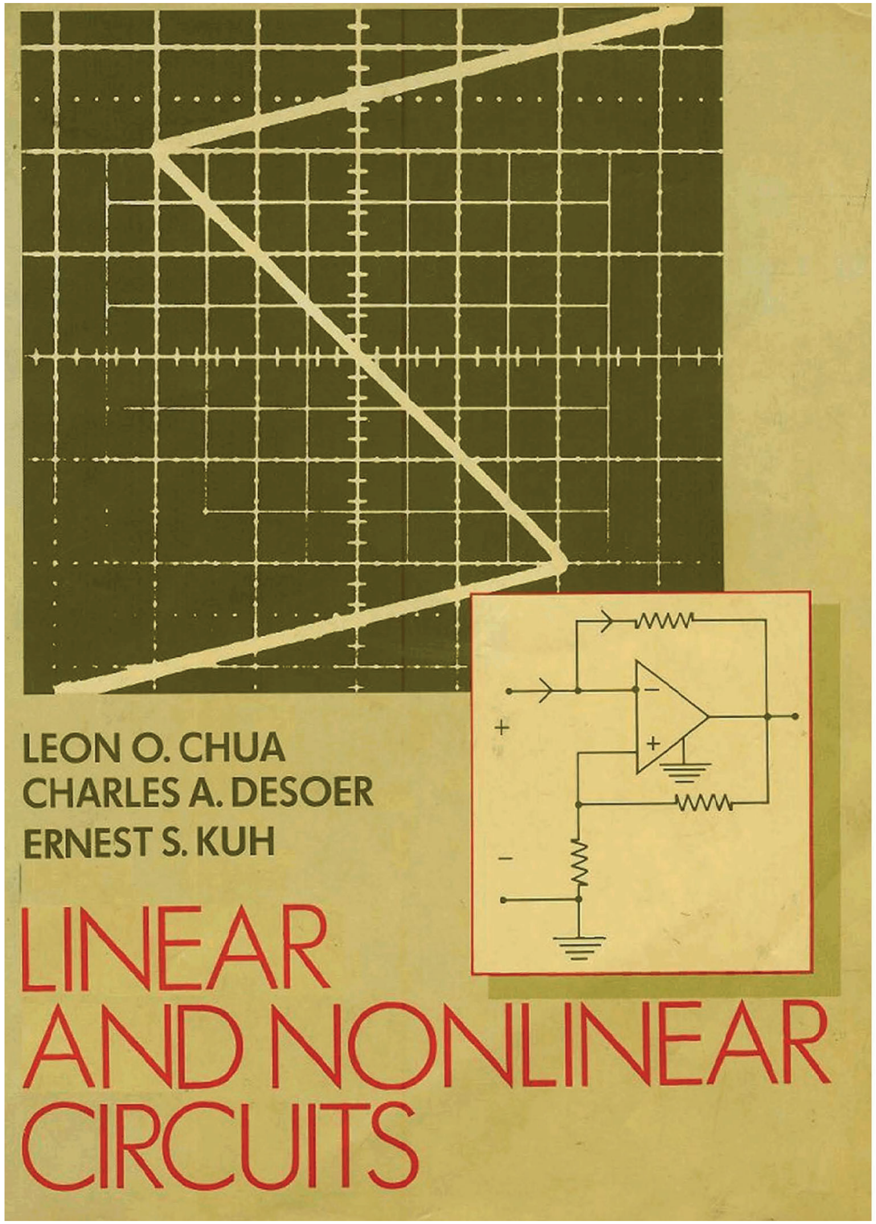


monotone controller (“lead-lag”)
reduces sensitivity



mixed-monotone controller
shapes ultra-sensitivity

The mixed feedback amplifier

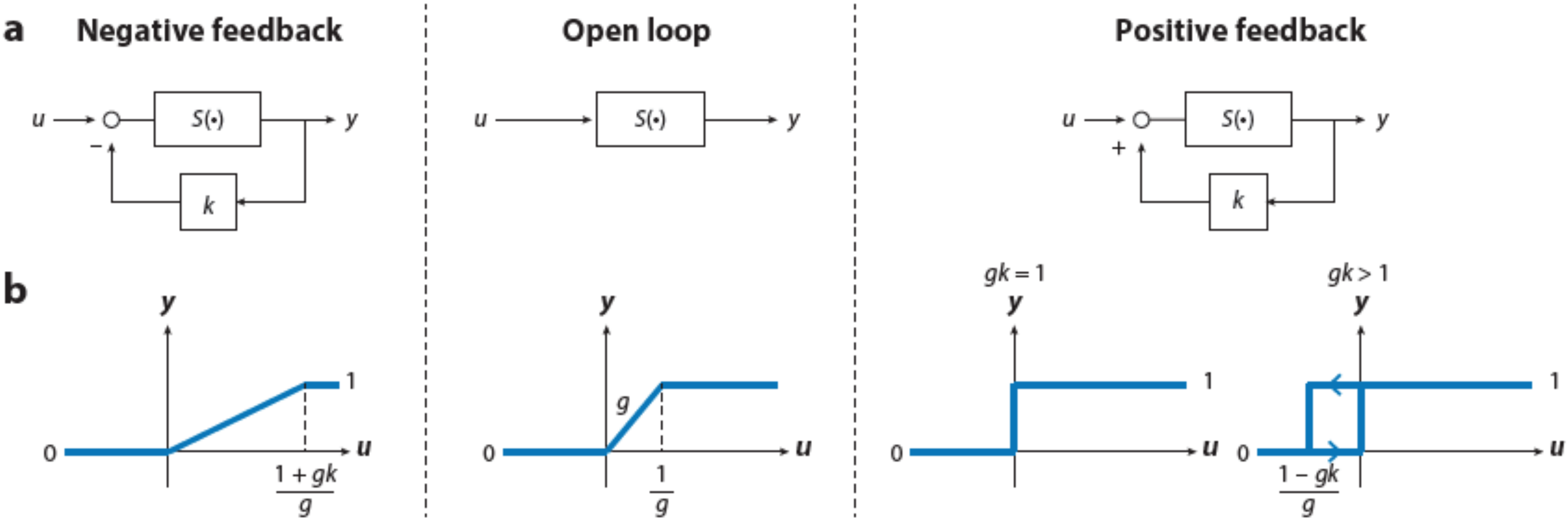


(1988)

The fundamental device
for switches and oscillations
in the pre-digital age

Why do we care ?

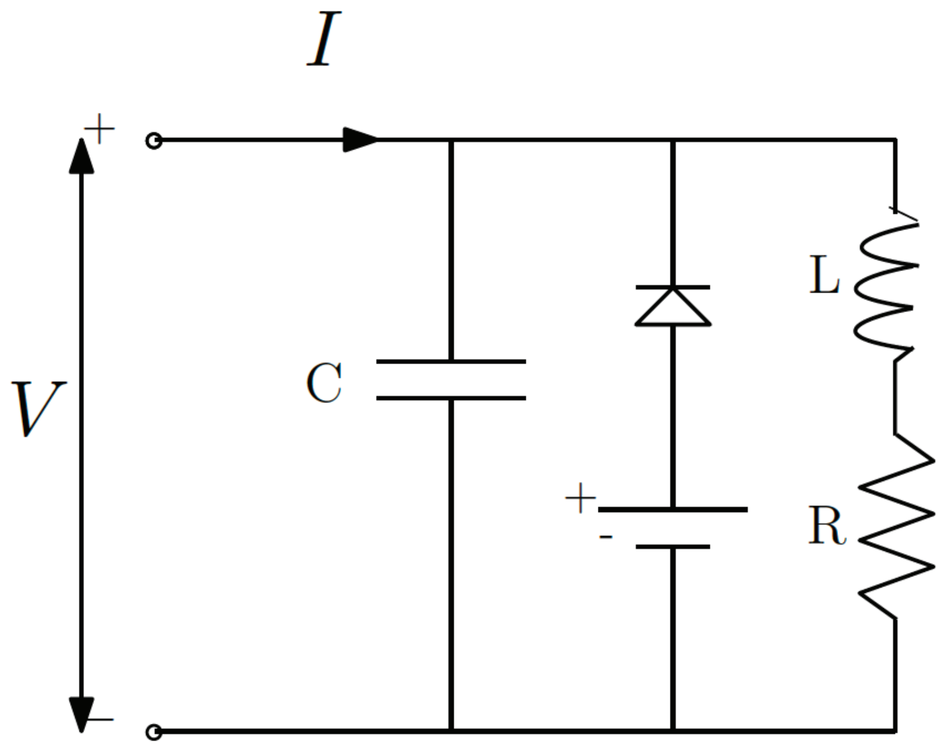
(Tedx Talk, 2014,
Annual Reviews 2018)



analog	−	amplifier	+	digital
tuning				switching
processing				memory

Mixed feedback acknowledges the mixed nature of spiking

Fitzhugh Nagumo circuit



$$
\begin{aligned}
C\dot{V} &= kV - \frac{V^3}{3} - I_L + I_{ext} \\
L\dot{I}_L &= -I_L + RV
\end{aligned}
$$

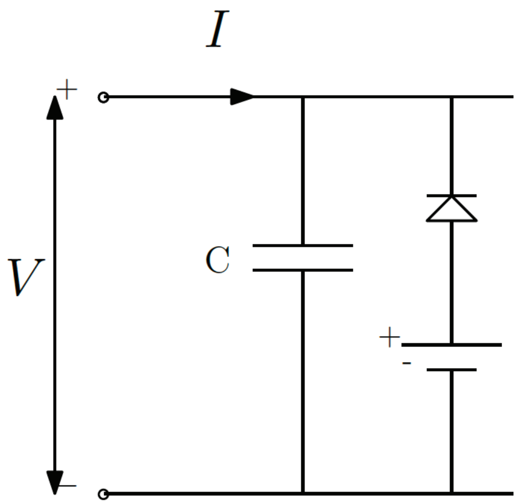
A circuit that reproduces the mechanism of nerve impulse:

R. FitzHugh, “Impulses and physiological states in theoretical models of nerve membrane,” Biophysical journal, vol. 1, no. 6, p. 445, 1961.

J. Nagumo, S. Arimoto, and S. Yoshizawa, “An active pulse transmission line simulating nerve axon,” Proceedings of the IRE, vol. 50, no. 10, pp. 2061–2070, 1962.

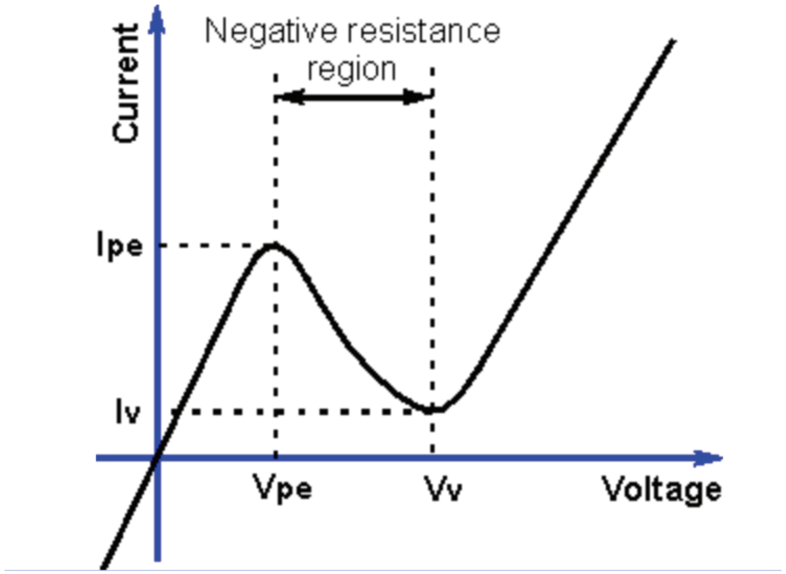
Referred to as “Bonhoeffer-van der Pol model” by FitzHugh after Van der Pol (1926).

The memory of FN circuit

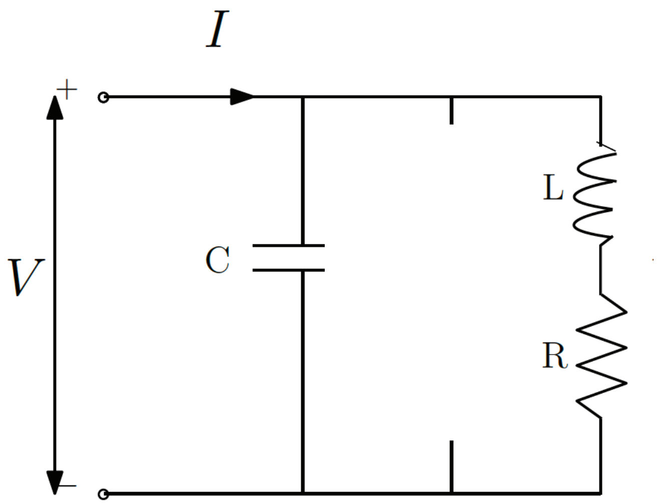


$$C\dot{V} = kV - \frac{V^3}{3} + I_{ext}$$

For a range of constant current,
bistable memory made of a capacitor (physical storage)
and a negative resistance device



The fading memory of FN circuit



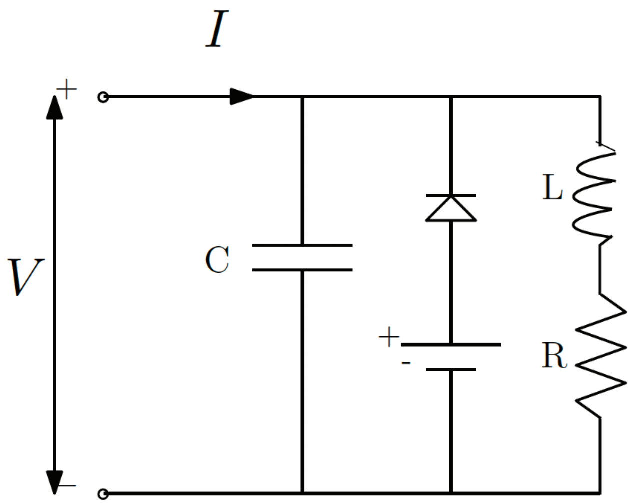
$$C\dot{V} = -I_L + I_{ext}$$
$$L\dot{I}_L = -I_L + RV$$

A RLC circuit has fading memory:
the effect of a current impulse fades out with time.

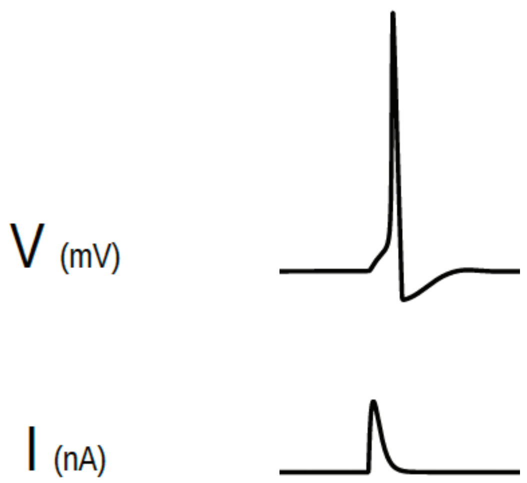
The elements R, L, and C, shape the fading memory

If the ration C/L is small, a current impulse charges the capacitor almost instantaneously, and the time constant L/R dictates the fading memory.

Spiking is a mixed mechanism



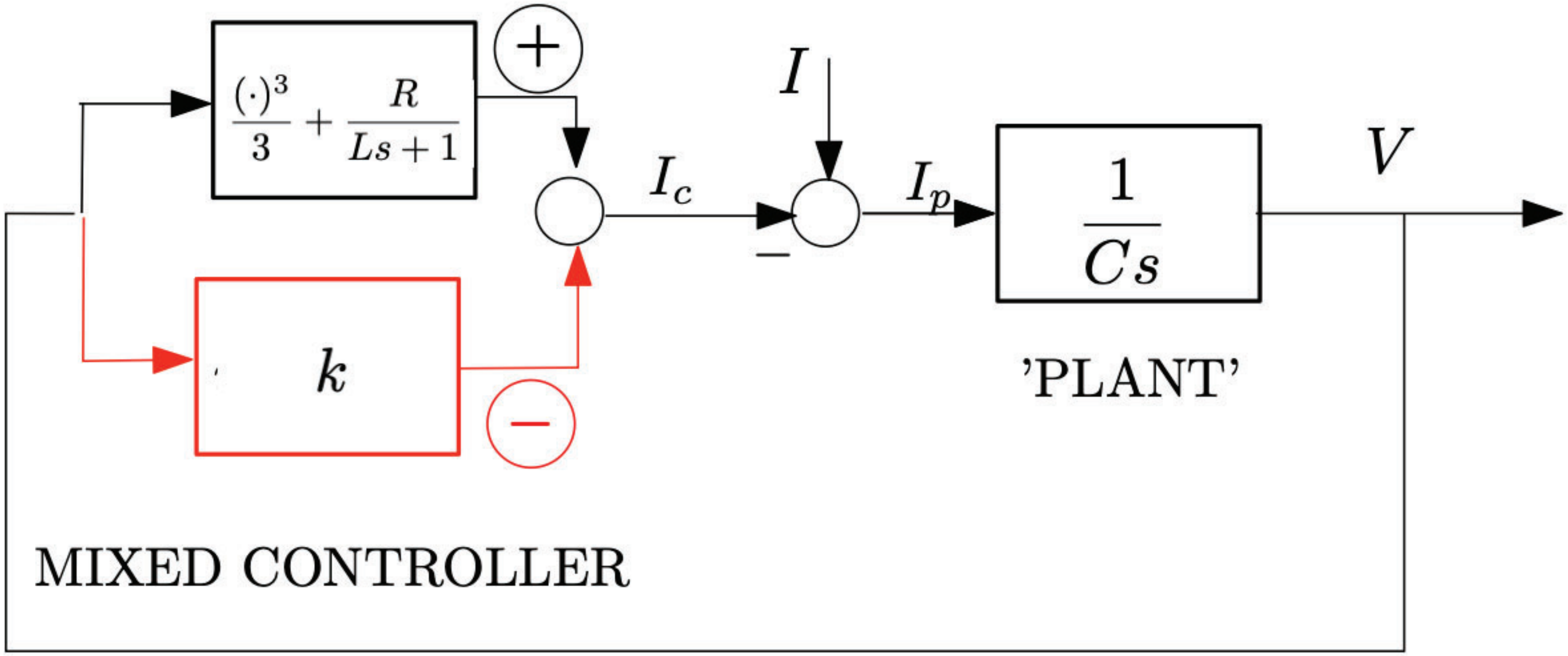
$$
\begin{aligned}
C\dot{V} &= kV - \frac{V^3}{3} - I_L + I_{ext} \\
L\dot{I}_L &= -I_L + RV
\end{aligned}
$$



Transient switch =
Memory at ‘fine’ scale
Fading memory at ‘coarse’ scale

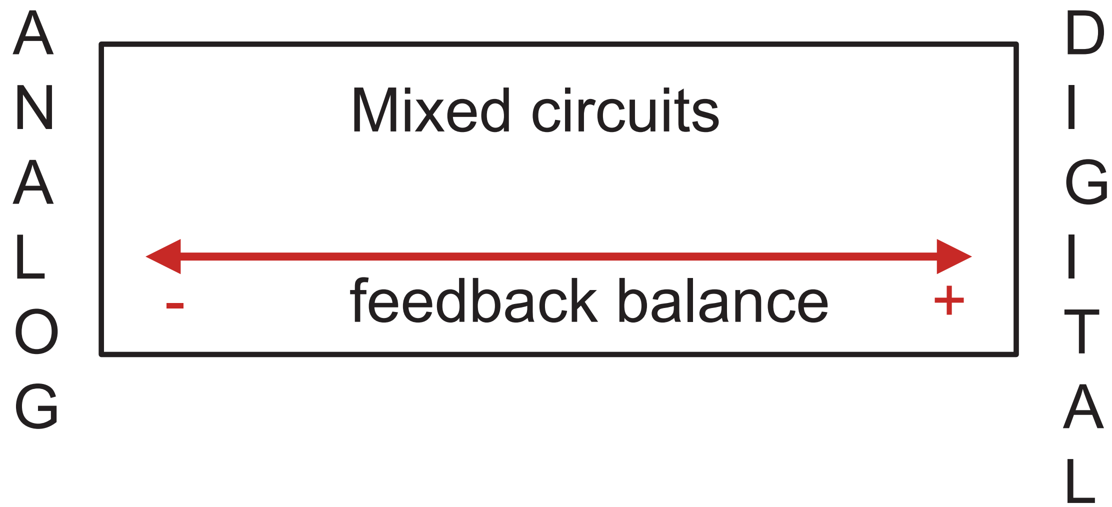
What is ‘scale’ ? A mixture of amplitude and time …

A mixed feedback representation of Fitzhugh Nagumo circuit



The negative feedback circuit has fading memory
The negative resistance = positive feedback = memory
The mixed feedback circuit has memory at fine scale
and fading memory at coarse scale

The neuromorphic promise



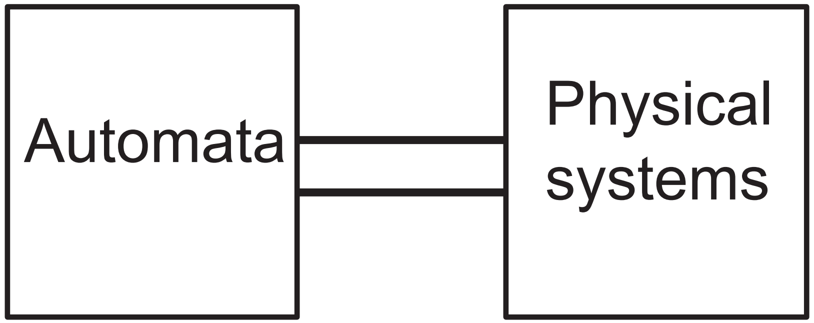
The mixed feedback amplifier is not the concatenation of an automaton and a physical system. It is a mixture of both.

Mixed feedback enables the combined reliability of the digital and adaptation of the analog

Mixed feedback enables control across scales.

Sepulchre, Drion, Franci. Annual Reviews 2018

Cyber-physical systems in the digital age



Cyberphysical systems interconnect elements that are *either* automata *or* physical systems

Added complexity of automata and physical systems.

Instead, spiking control systems interconnect *mixed* elements, that are *both* physical and algorithmic.

Mixed control systems inherit the tractability of classical control theory.

Today’s talk

- An academic example of spiking control
- Event-based automation
- Event-based regulation

IEEE CONTROL SYSTEMS LETTERS, VOL. 8, 2024

Neuromorphic Control of a Pendulum

Raphael Schmetterling, *Graduate Student Member, IEEE*, Fulvio Forni, *Senior Member, IEEE*, Alessio Franci, and Rodolphe Sepulchre, *Fellow, IEEE*

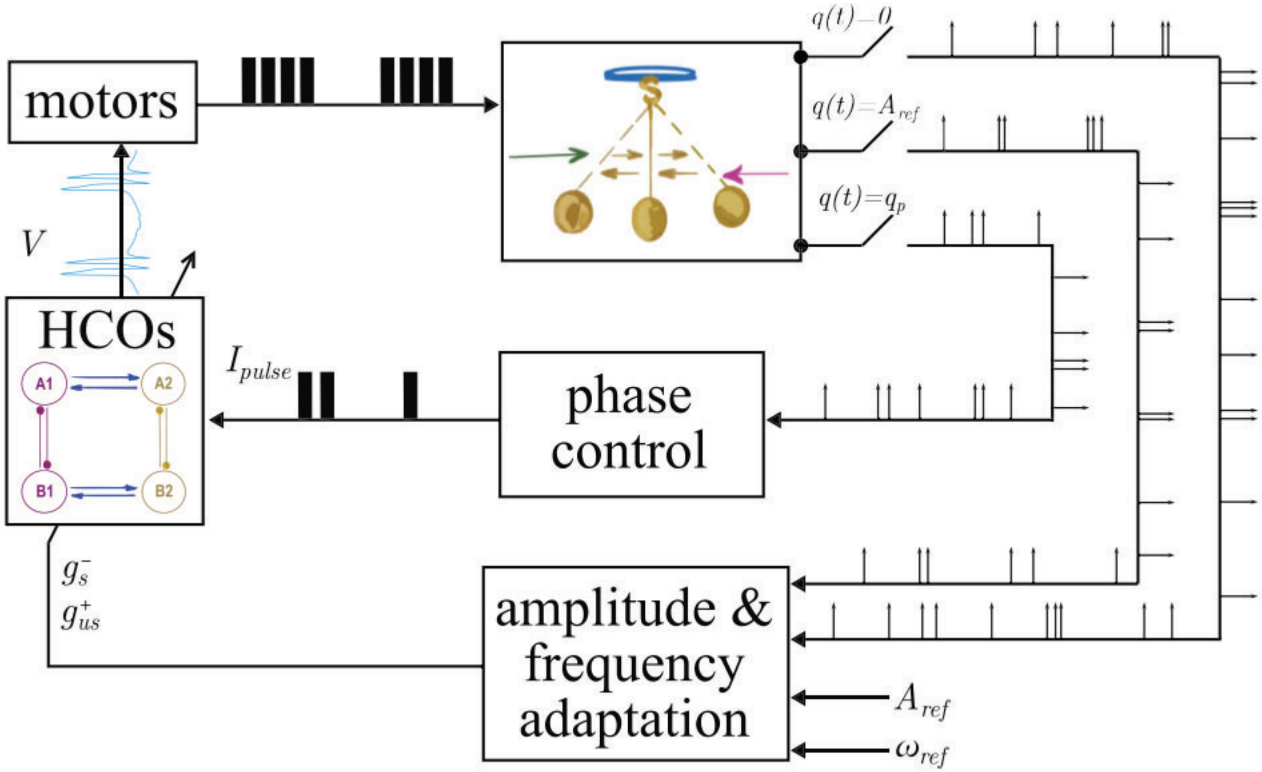


Fig. 4. Block diagram of the complete architecture, including the event-based feedback loops introduced in Sections VI and VII. Small arrows over signal transmission lines indicate event-based communication as described in Section III. The HCO block architecture is described in Sections III and IV.

Controlling when and where needed …

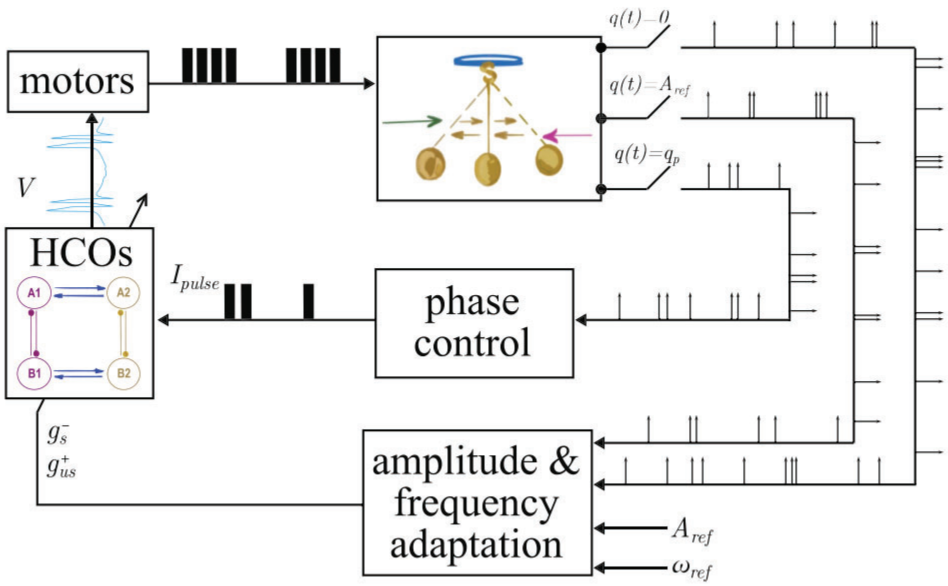


Fig. 4. Block diagram of the complete architecture, including the event-based feedback loops introduced in Sections VI and VII. Small arrows over signal transmission lines indicate event-based communication as described in Section III. The HCO block architecture is described in Sections III and IV.

How *often* do you need to interact with a pendulum to control it ?

How *energy efficient* can you make a control system ?

How to make a control law *soft* yet *accurate ?*

How to make control design inherently *distributed* and *redundant ?*

Efficient control, RS, IEEE Control Systems, October 2024

Ingredients of a neuromorphic design

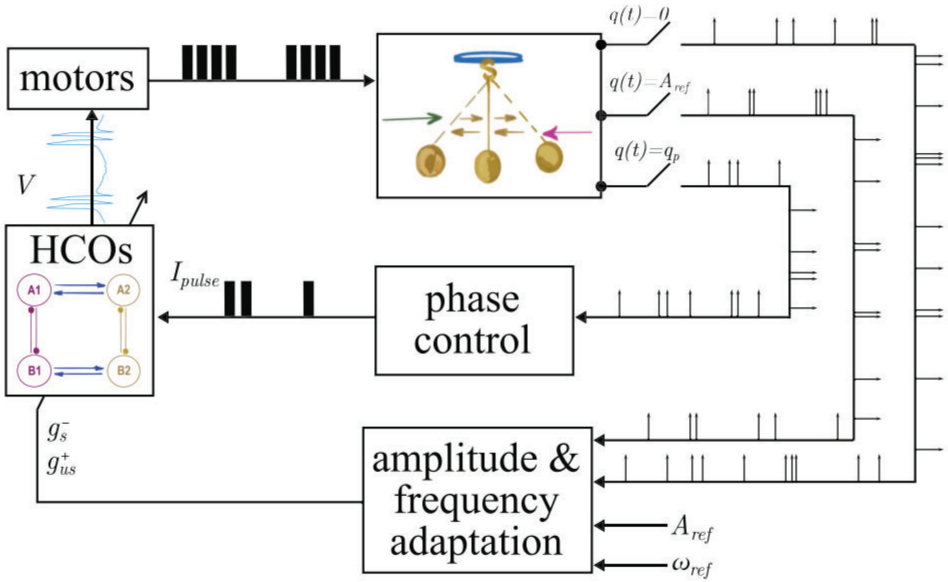


Fig. 4. Block diagram of the complete architecture, including the event-based feedback loops introduced in Sections VI and VII. Small arrows over signal transmission lines indicate event-based communication as described in Section III. The HCO block architecture is described in Sections III and IV.

Feedforward module : a rhythmic automaton

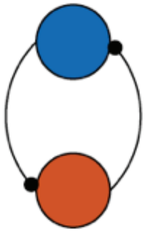
Adaptation module : a tunable automaton

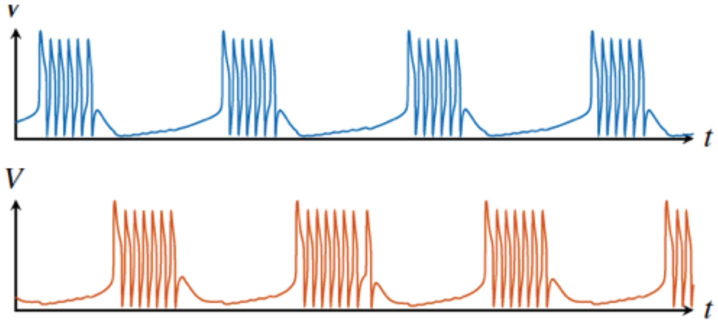
Key feature: *co-design* of the automaton and the regulator

Today’s talk

- An academic example of spiking control
- Event-based automation
- Event-based regulation

The automaton of a periodic sequence



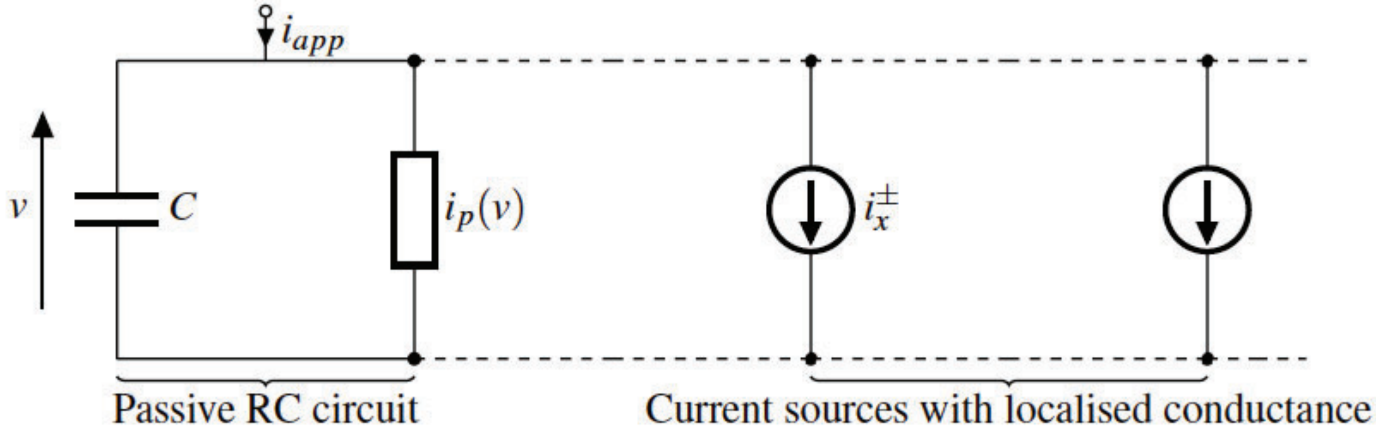


The Half-Center-Oscillator: the harmonic oscillator of biology

Inter-burst frequency determines the frequency of the oscillator

Intra-burst frequency determines the energy of the events

Biological inspiration



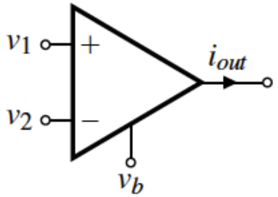
A neuron is modelled as a “two-terminal one port” electrical circuit.

A leaky memory (RC) in parallel with a bank of current sources

Each current source has localised conductance

Current sources are mixed : they come by pairs

Neuromorphic circuit primitives



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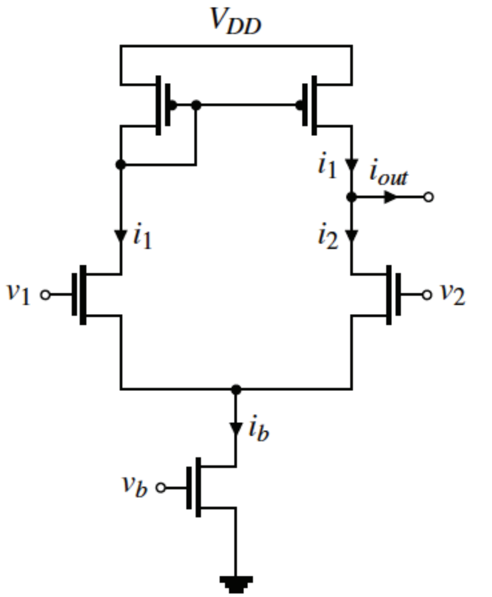
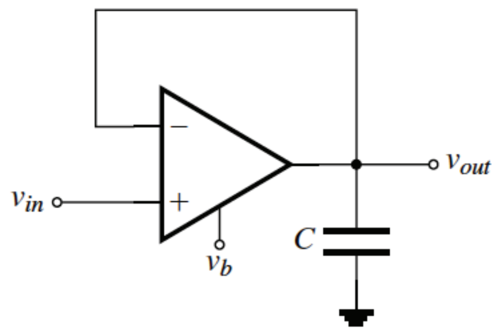


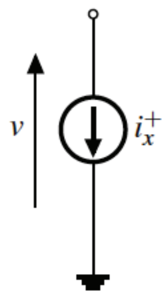
$$i_{out} = i_1 - i_2 = i_b \tanh\left(\kappa \frac{v_1 - v_2}{2v_T}\right)$$

localisation in amplitude



$$C\frac{dv_{out}}{dt} \approx \frac{i_b \kappa}{2v_T}(v_{in} - v_{out})$$

localisation in time



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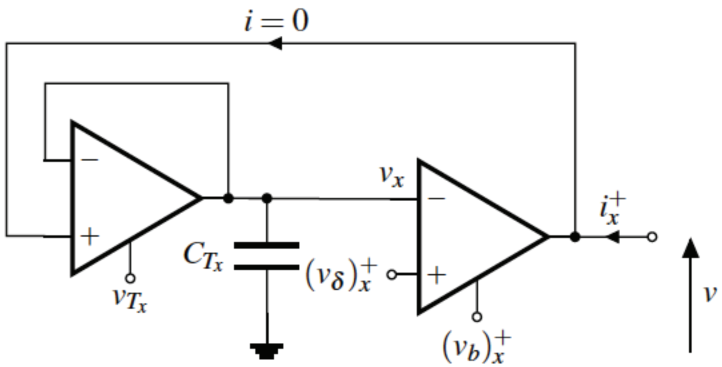
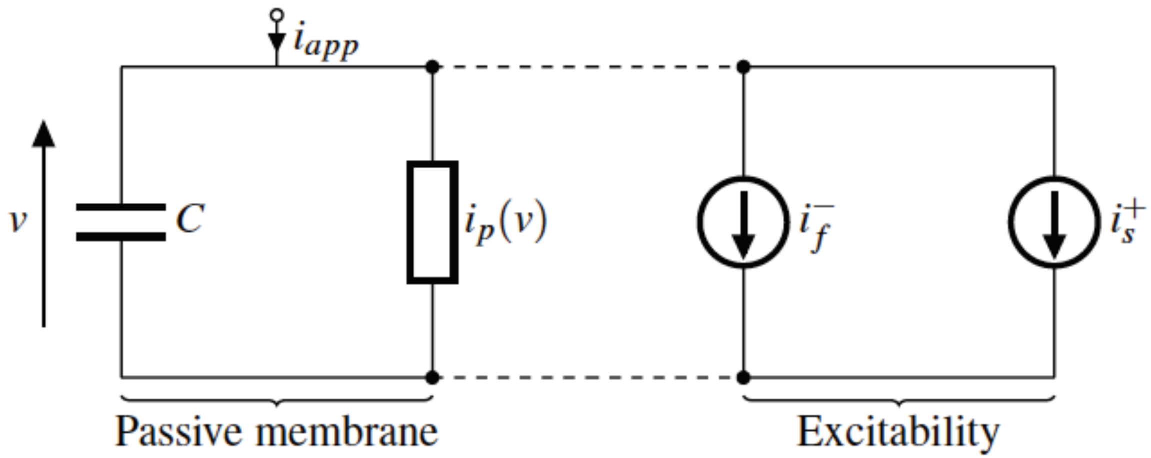


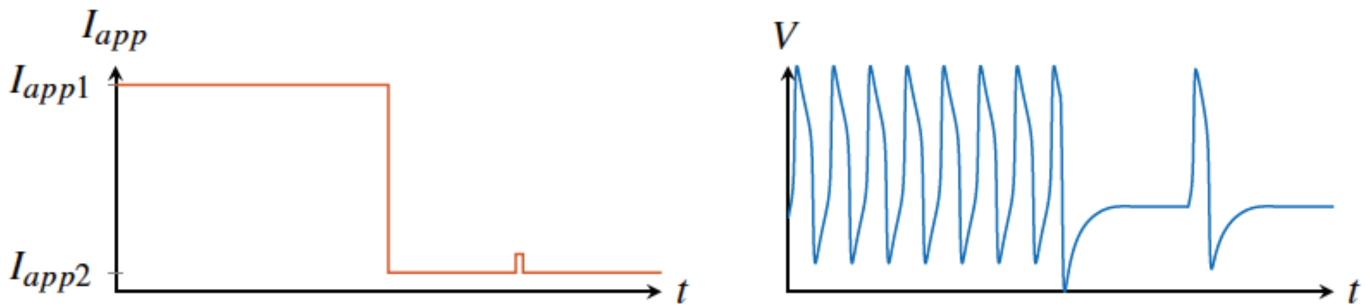
$$i_x^{\pm} = \pm(i_b)_x^{\pm} \tanh\left(\kappa \frac{v_x - (v_\delta)_x^{\pm}}{2v_T}\right)$$

$$C_{T_x}\dot{v}_x = i_{T_x} \tanh\left(\kappa \frac{v - v_x}{2v_T}\right)$$

localisation in amplitude and time

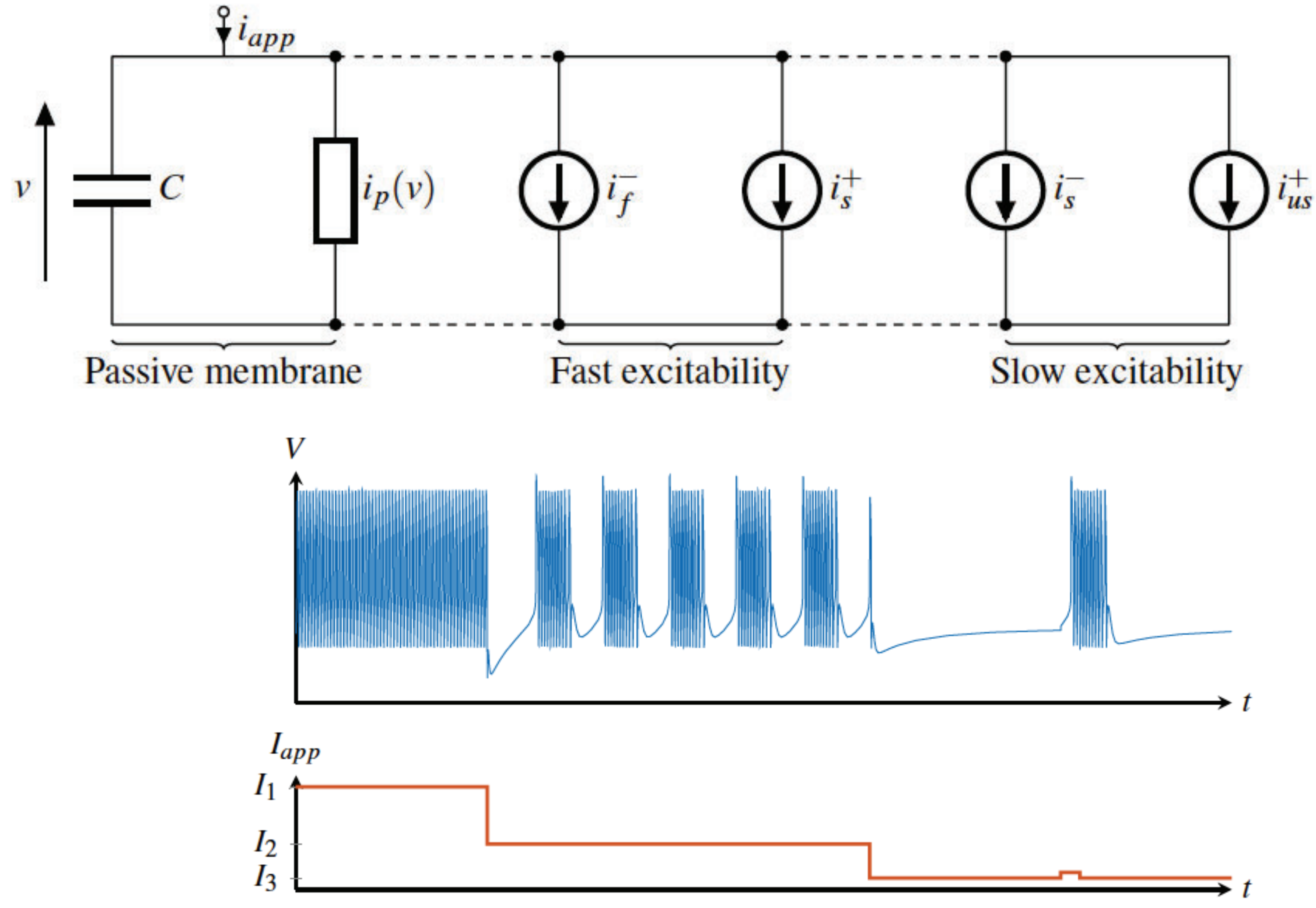
Spiking neuron





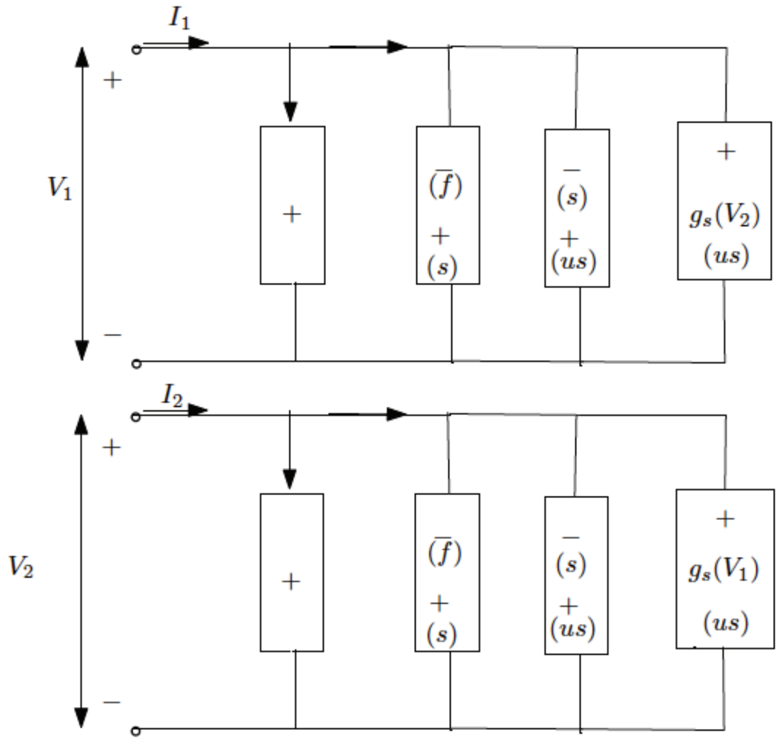
Ribar & Sepulchre, 2021

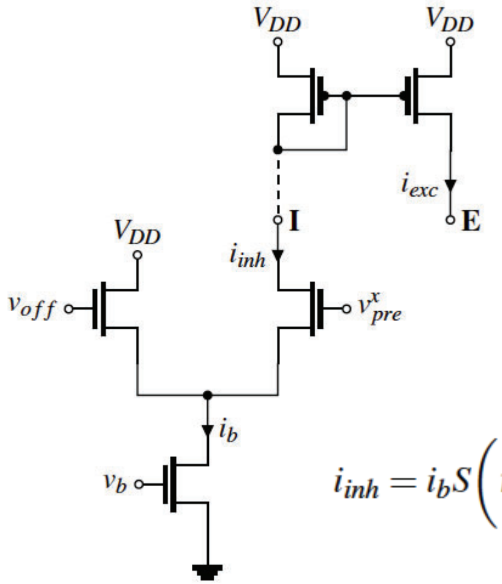
Bursting circuit



Ribar & Sepulchre, 2021

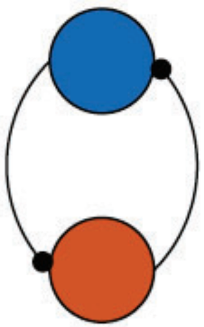
Oscillator circuit

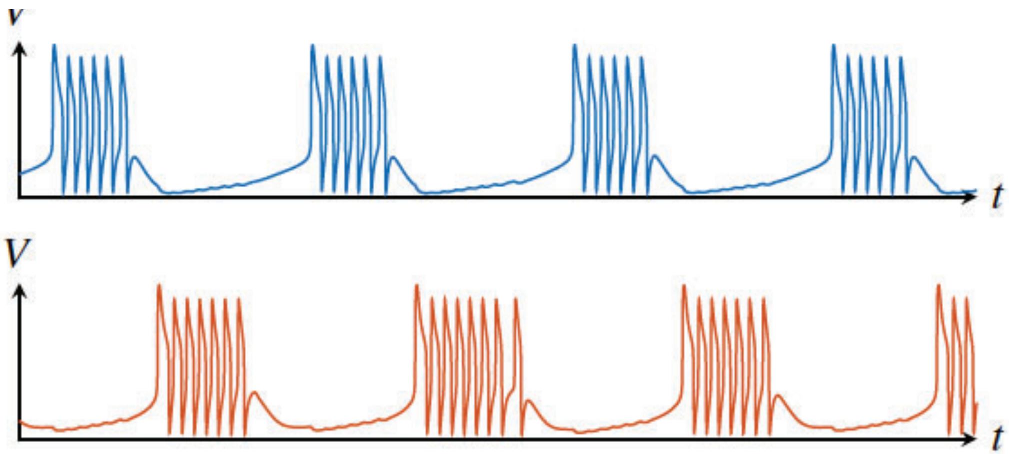




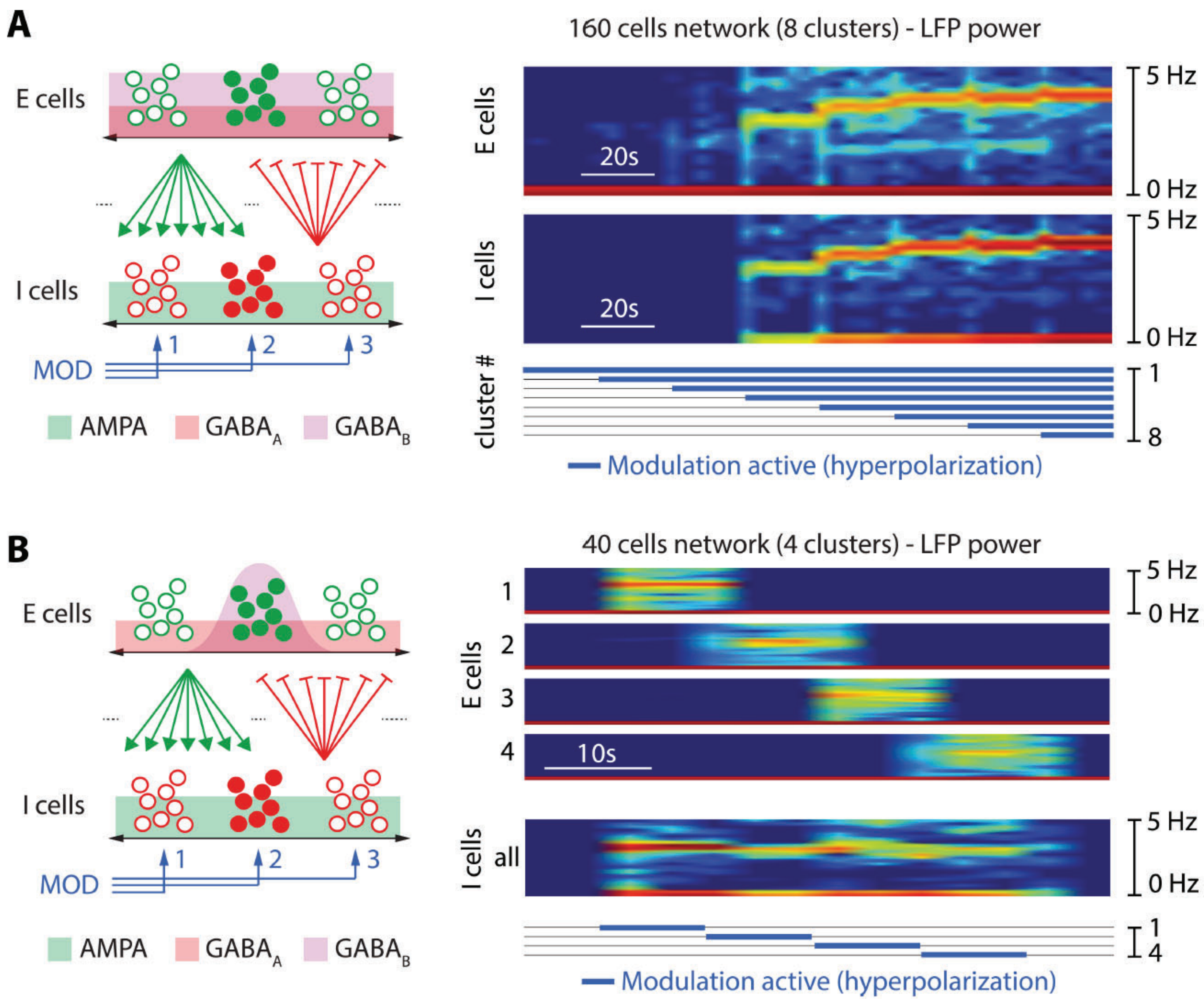
$$i_{inh} = i_b S\left(\kappa \frac{v^x_{pre} - v_{off}}{v_T}\right)$$

synaptic current source





Spatio-temporal network ‘states’

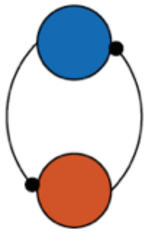


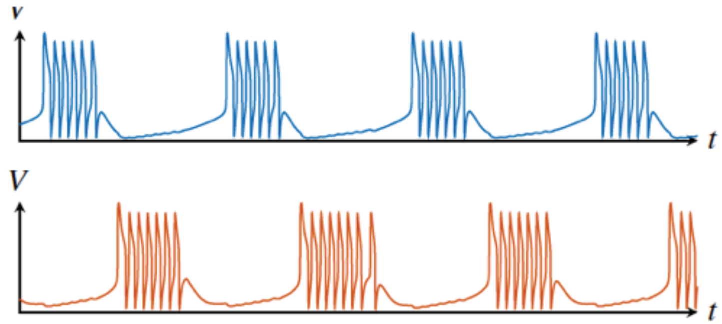
Drion, Francis, Sepulchre, Plos 2018

Today’s talk

- An academic example of spiking control
- Event-based automation
- Event-based regulation

The regulation of a periodic sequence





Inter-burst frequency determines the frequency of the oscillator

Intra-burst frequency determines the energy of the events

Neuromodulation of an oscillator

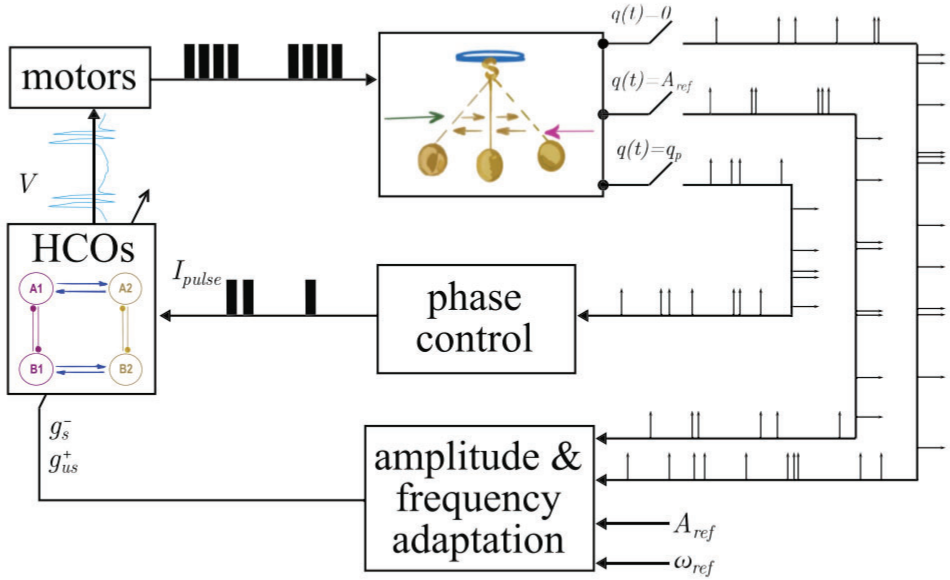


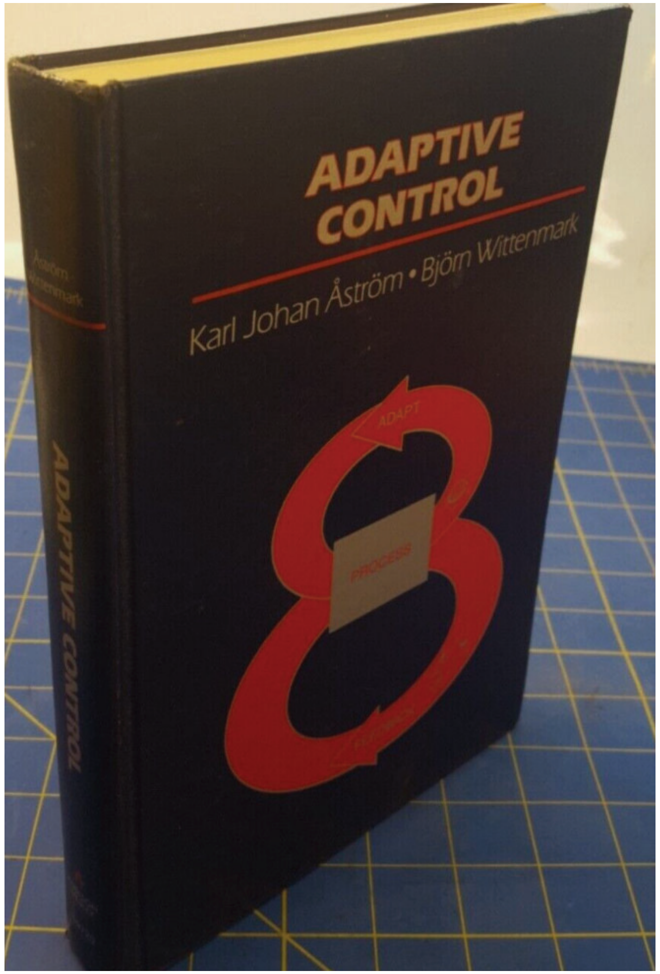
Fig. 4. Block diagram of the complete architecture, including the event-based feedback loops introduced in Sections VI and VII. Small arrows over signal transmission lines indicate event-based communication as described in Section III. The HCO block architecture is described in Sections III and IV.

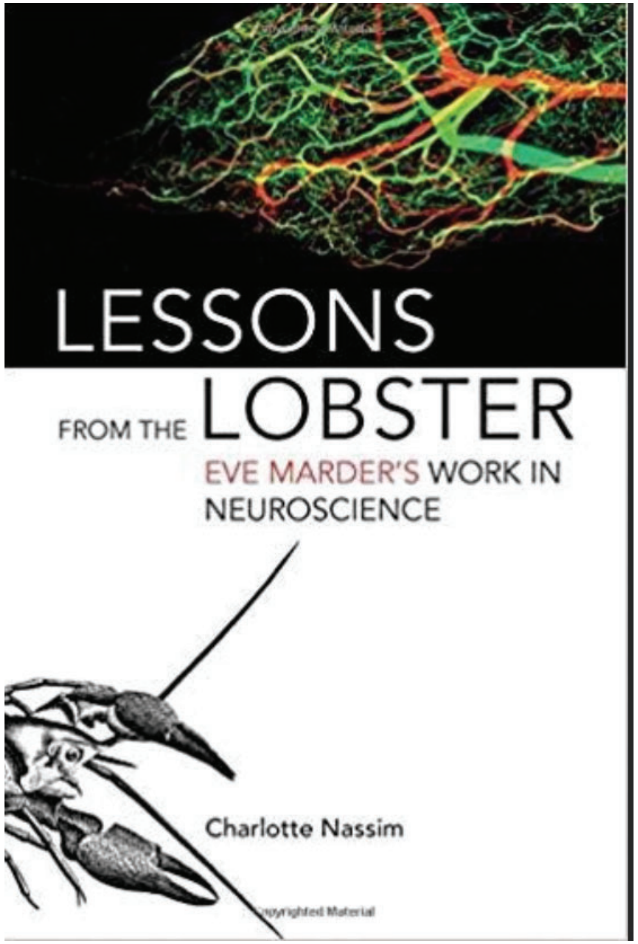
Modulate the intra-burst or inter-burst frequency by adaptive control

= ‘integral’ feedback of classical control

Neuromorphic Learning: Opportunities

Neuromorphic learning = adaptive control = neuromodulation





50 years of research in engineering and in neuroscience to leverage from …

Adaptive Control

Chapter 1 What Is Adaptive Control?

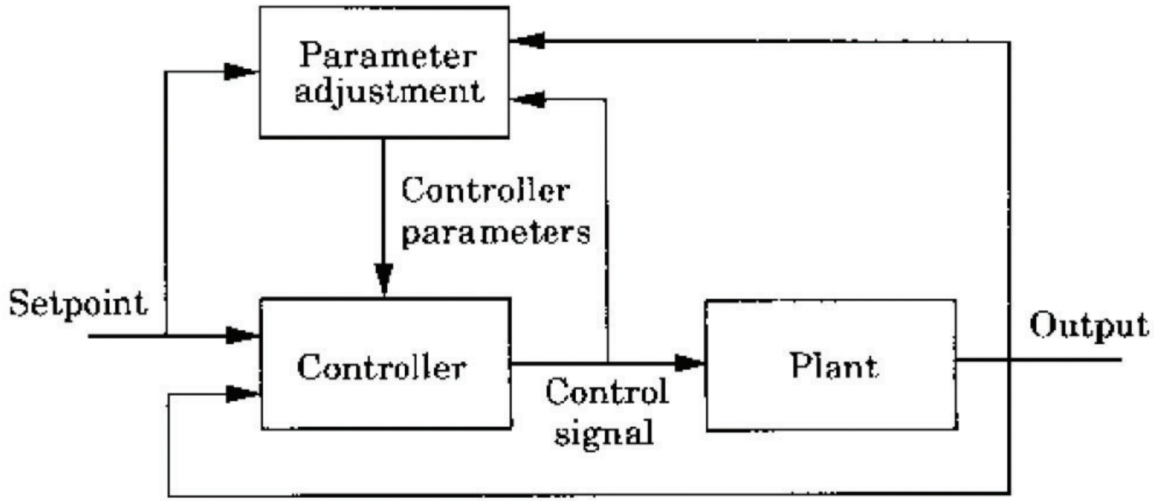
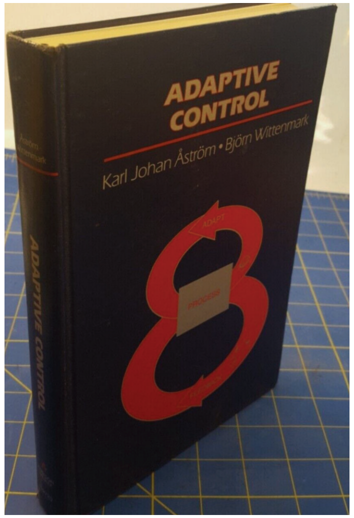


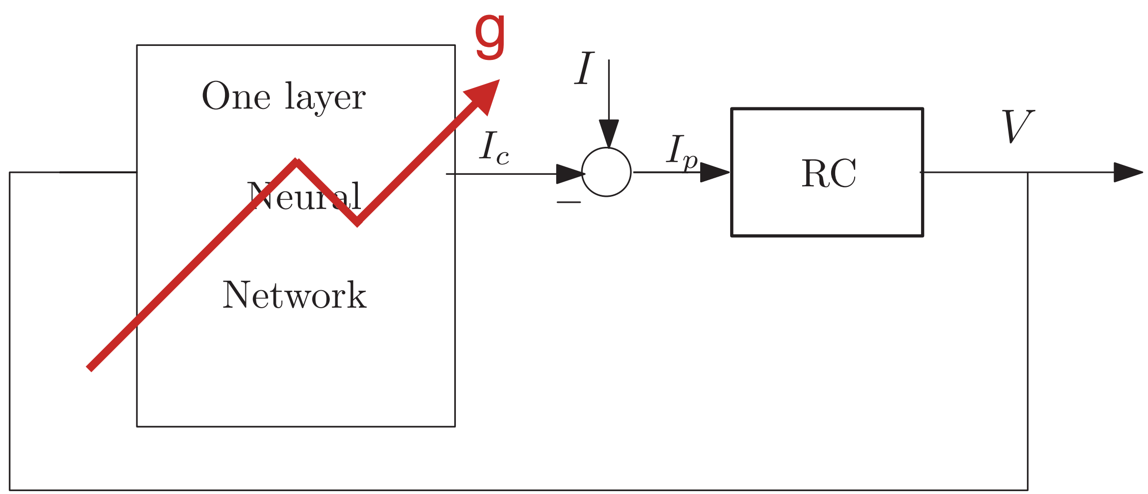
Figure 1.1 Block diagram of an adaptive system.



A theory developed in the 70s for linear systems.

The starting point :
Adaption (= Learning) is ‘easy’ under three conditions :
(i) linear parametrisation (ii) stable inverse (iii) relative degree one

Mixed feedback circuits are “easy” to adapt



The starting point :

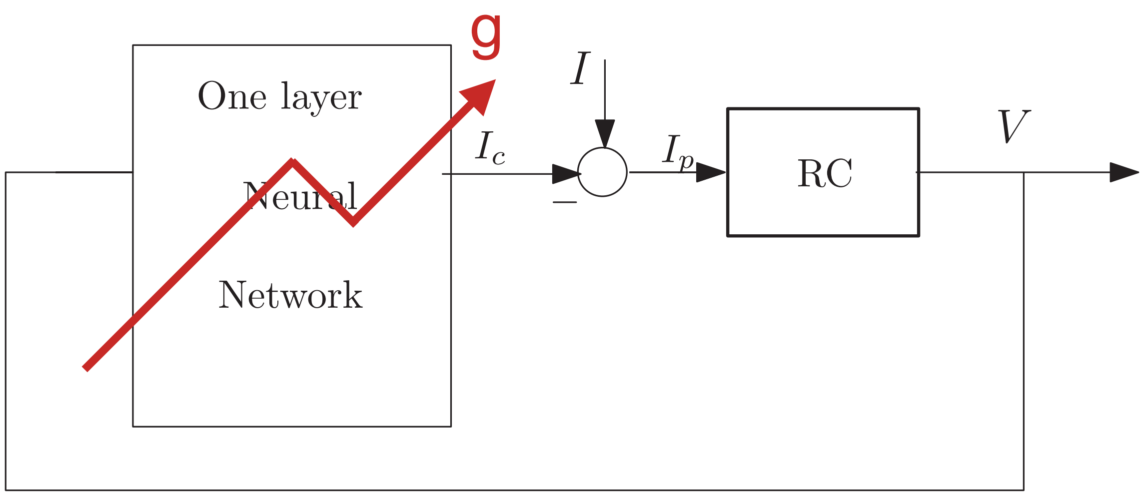
Adaption (= Learning) is ‘easy’ under three conditions :

(i) linear parametrisation : maximal conductances

(ii) stable inverse : I = difference of monotone (V)

(iii) relative degree one: RC has relative degree one !

Model reference Adaptive Control



Consider a reference trajectory $(I(\cdot), V_{ref}(\cdot))$
generated by a reference conductance g_{ref}

The learning rule is a linear regressor driven by the prediction error

$$e(t) = V_{ref}(t) - V(t)$$

A realm of learning rules

Recursive Least Squares estimation (RLS)

Least Mean Square estimation (LMS)

Stochastic gradient

MIT rule

Hebbian learning

…

All those learning rules proceed from (approximately) regressing the linear parameters from the residual error.

Simplifications rely on time-scale separation and distributed computation.

‘Continuous’ regulation is *unreliable*

A pillar of regulation theory is the internal model principle:

An external signal can be *robustly* asymptotically regulated only if the regulator can generate this signal *internally.*

For ‘continuous’ regulation, the internal model principle is a calibration principle: exact regulation requires exact calibration of the internal model.

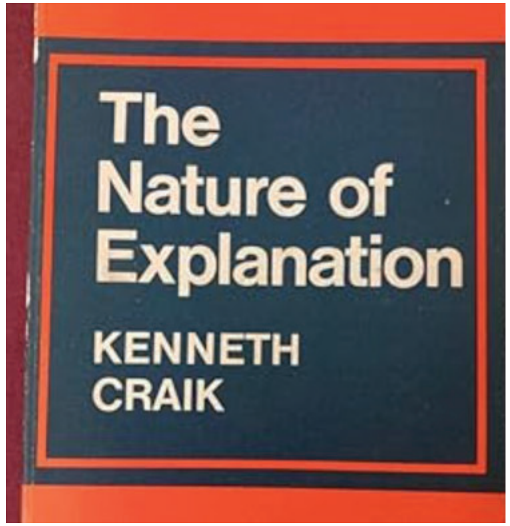
Regulation is good for adaptation, but continuous regulation is *unreliable*

An event-based internal model principle

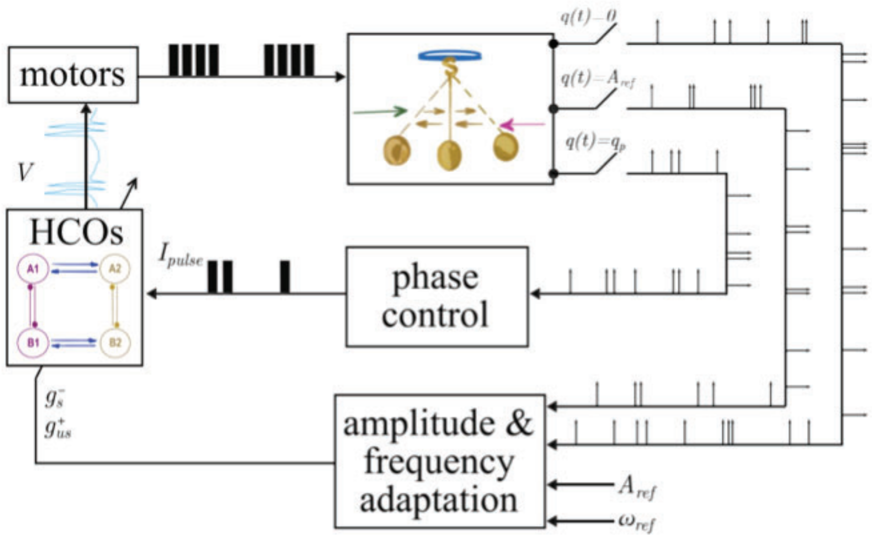
The original formulation of the internal principle refers to “events”, NOT to “continuous trajectories”:

Only an internal model of reality - this working model in our minds- enables us to predict ***events*** *which have not yet occured in the physical world, a process which saves time, expense, and even life. In other words the nervous system is viewed as a calculating machine capable of modelling or paralleling external* ***events****, and this process of paralleling is the basic feature of thought and of explanation*

Kenneth Craik’s, The Nature of Explanation (1943)

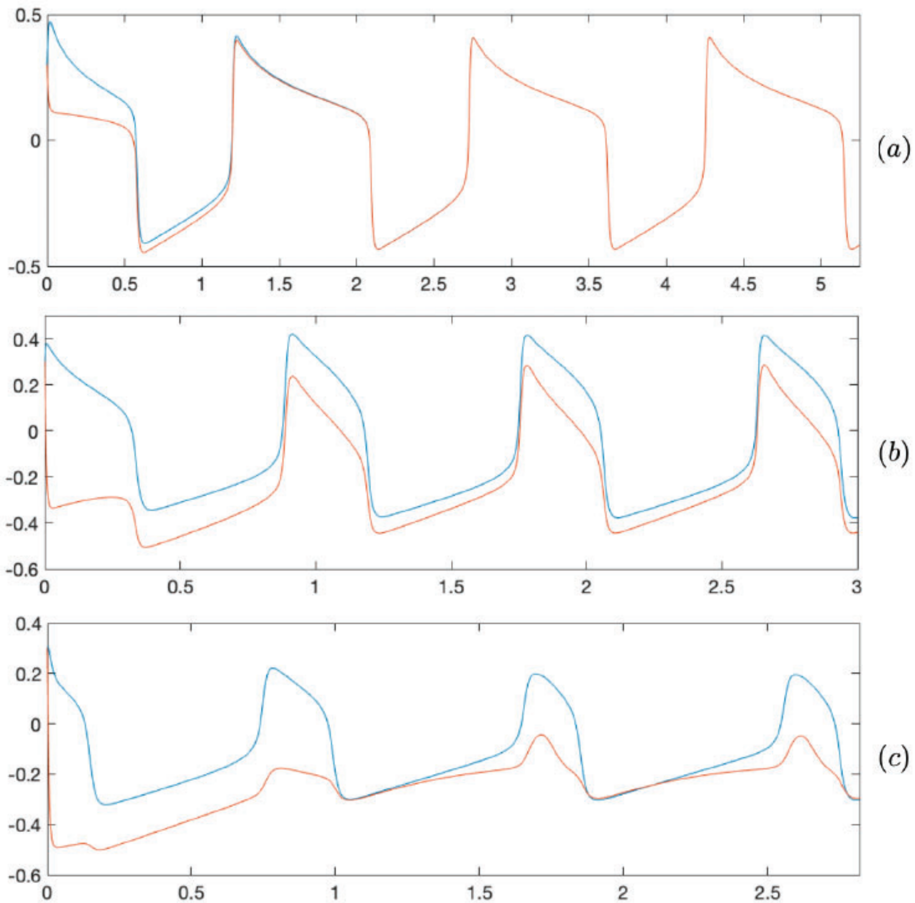


An academic example of event-based regulation



- The internal model does not need to generate the external trajectories, but only the external events
- The generator of events is a physical neuromorphic circuit. Easily calibrated.
- A possible reconciliation between control theory and neuroscience…

Synchrony without calibration



Event synchrony

Continuous synchrony

Fig. 1. Rapid synchronization of two identical (a) and non-identical (b) excitable systems under weak excitatory synaptic coupling. (c) Poor synchronization of the same non-identical excitable systems under strong diffusive coupling.

Rapid and robust synchronization via weak synaptic coupling, J.-G. Lee, RS, Automatica, 2024

Event-based learning = regulation without calibration !

The reliability experiment

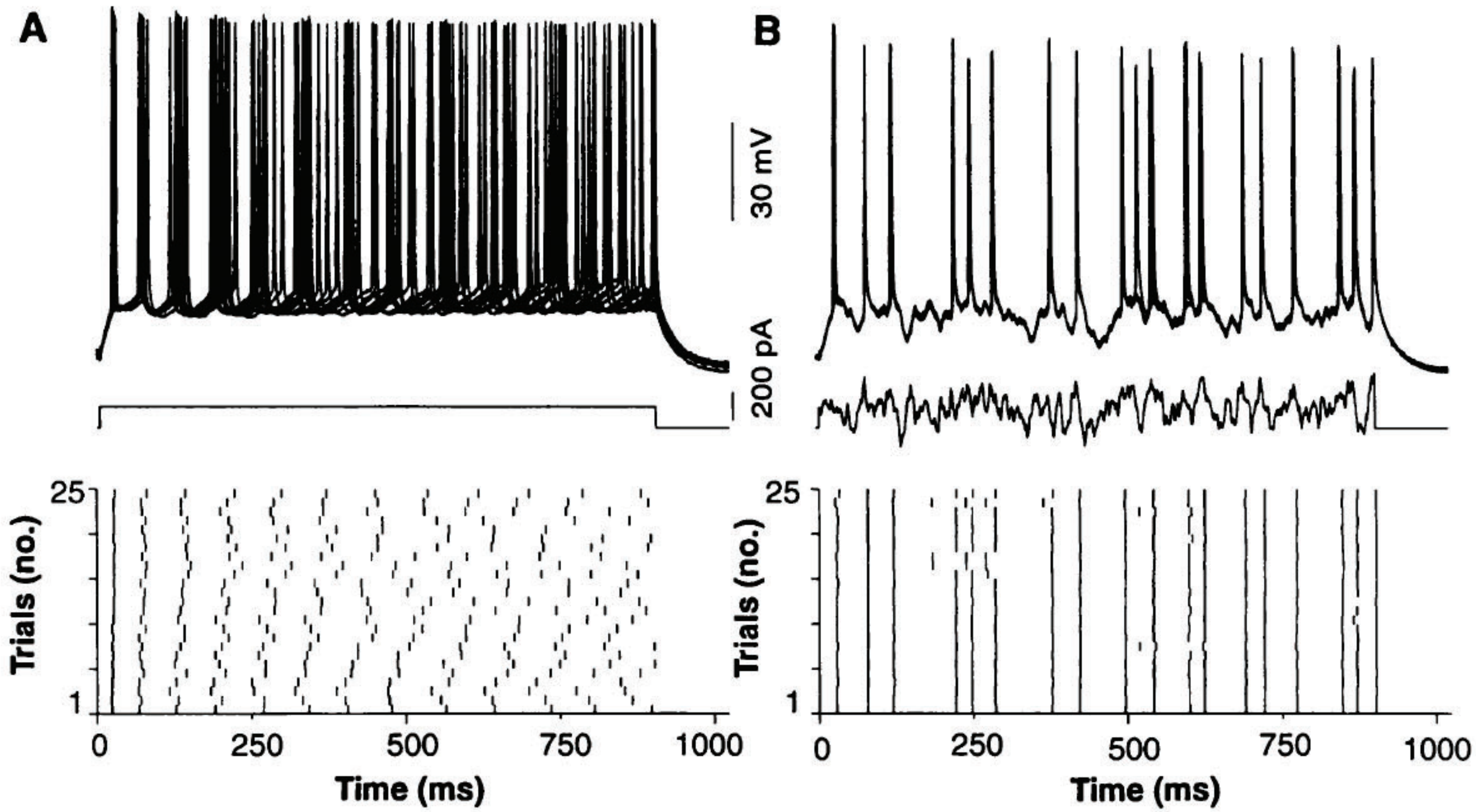
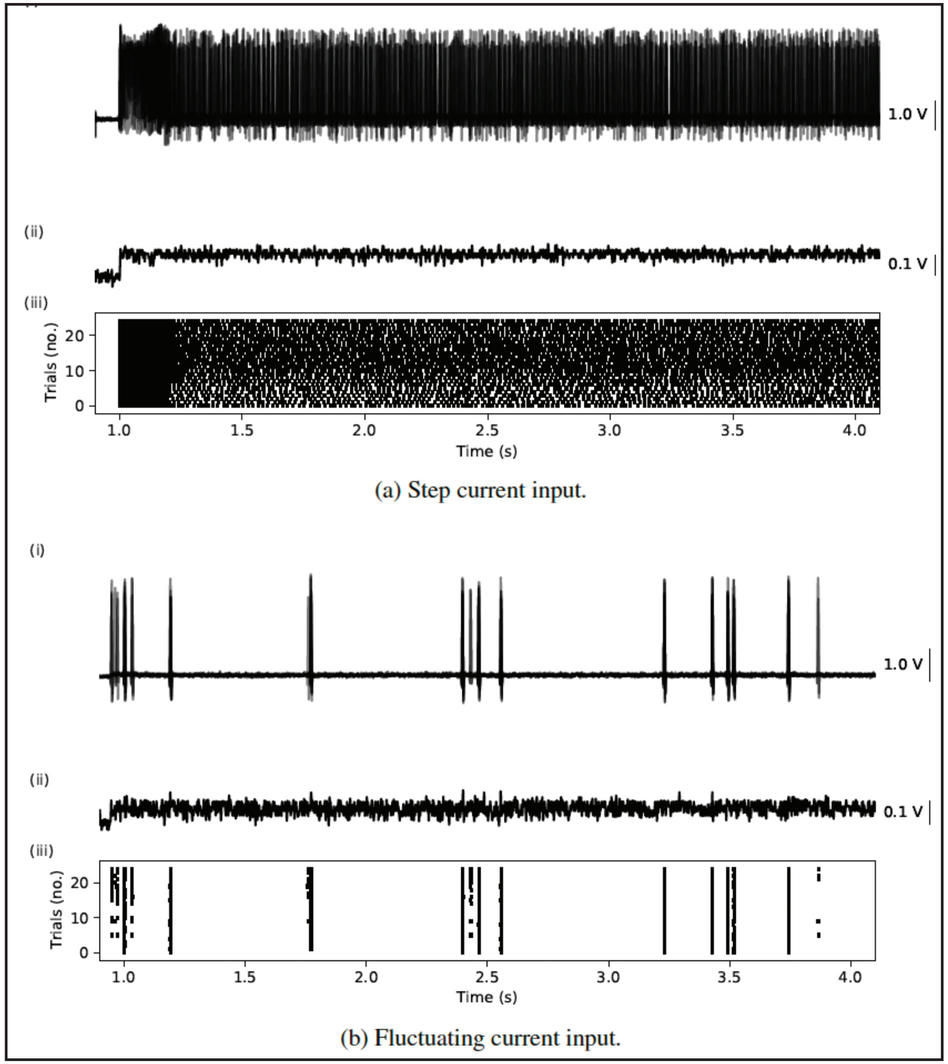


Fig. 1. Reliability of firing patterns of cortical neurons evoked by constant and fluctuating current. (**A**) In this example, a superthreshold dc current pulse (150 pA, 900 ms; middle) evoked trains of action potentials (approximately 14 Hz) in a regular-firing layer-5 neuron. Responses are shown superimposed (first 10 trials, top) and as a raster plot of spike times over spike times (25 consecutive trials, bottom). (**B**) The same cell as in (A) was again stimulated repeatedly, but this time with a fluctuating stimulus [Gaussian white noise, μ_s = 150 pA, σ_s = 100 pA, τ_s = 3 ms; see (*14*)].

Mainen & Sejnowski, Science, 1995

Event-regulation can be made reliable !

The reliability experiment in silico



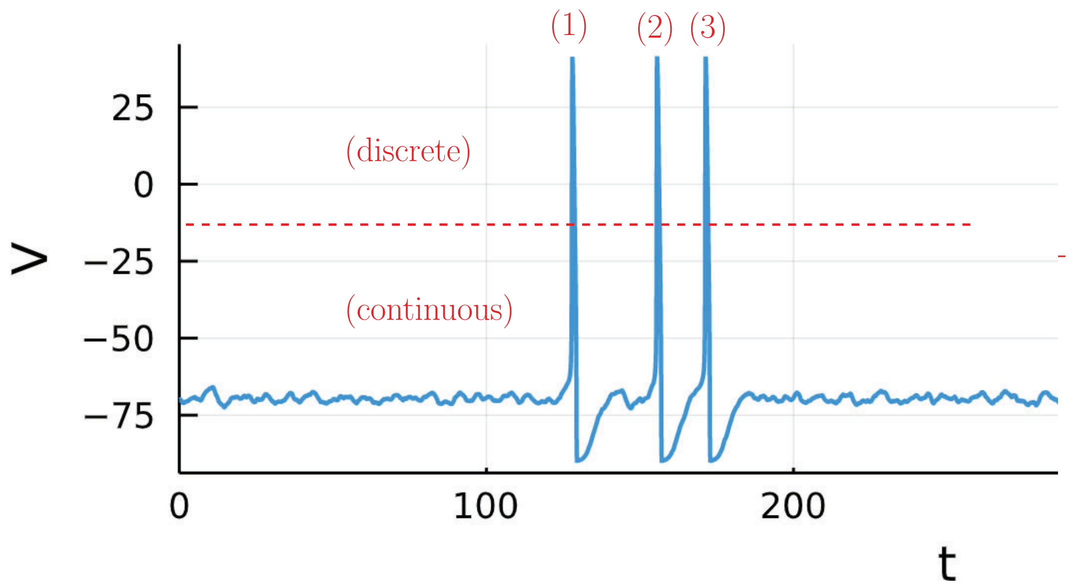
Kirby, Ribar & Sepulchre, unpublished, 2022

Neuromorphic regulation can be made reliable !

Today’s talk

- An academic example of spiking control
- Event-based automation
- Event-based regulation
- Concluding remarks

Spiking Control Systems



Spiking is the result of *mixed* feedback control.

Positive feedback is necessary for automation: memory, decision-making.

Negative feedback is necessary for regulation: fading memory, adaptation.

Mixed feedback enables reliability AND adaptation

Neuromorphic control

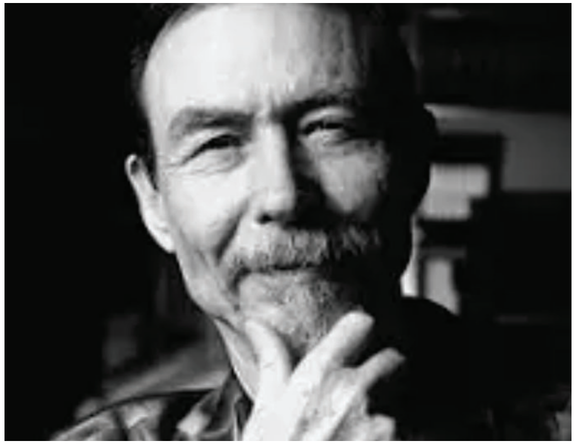
- Neuromorphic control is mixed:
  co-design of automation and regulation
- The *automaton* is a physical circuit that generates discrete *events*
- The *regulator* is a feedback loop that endows the automaton with adaptation and learning capabilities

Reconciling physics and algorithmics ?

Physics	*Physical Computation*	*Algorithmics*
Physical	Neuromorphic	Computational
Continuous	Event-based	Discrete
EE	Bio-inspired	CS
Odes	Spiking	Automata
Analysis	Convex-concave	Logics
Signals	Events	Data
Circuits	Interactions	Graphs
19th century	21th century ?	20th century

Physical computation

Carver Mead



Neuromorphic computing

A machine that awaits a theory

Richard Feynman

Quantum computing

A theory that awaits a machine

John Hopfield

Collective computing

A theory that awaits a theory

Spiking Intelligence

- There is no intelligence without feedback.
- Spiking is the result of mixed feedback.
- Mixed feedback technology aims at addressing the AI gap.